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Application of LANDSAT-1 data to crop area and yield estimates, forest identification, and soil classification in Iowa

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Application of LANDSAT-1 data to crop area and yield estimates, forest identification, and soil classification in Iowa

by

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INTRODUCTION

As world population increases and hence the demand for food, the need for regional, national, and worldwide agricultural resource surveys is greater than ever before. Adequate planning of international and domestic policies and actions regarding food reserves is very much dependent on the availability of accurate production forecasts. Food market prices tend to be more stable and all facilities concerned with storage, transportation, and processing are used more efficiently when there is reliable advance knowledge of what harvest will provide. The quality of this information has become critical at all levels of management. Traditional sampling methods used to gather agricultural production information are time consuming, they require many trained personnel, and the results are sometimes not fully reliable. In addition, these surveys sometimes lag behind the needs of the decision makers.

There is ample evidence at the present time that modern remote sensing activities can successfully be applied to the direct benefit of humanity. The rapid evaluation of the earth's features and resources, which multispectral scanners make possible, can provide needed quantitative agricultural data. This technology is based on the measurement of radiation either reflected from or emitted from the earth's surface. Aircraft or satellite sensing platforms are used to acquire this data. Data from large terrestrial areas can be assigned into a limited number of discrete categories which can aid in the inventory and planning of agricultural activities. The repetitive coverage provided by the sensing systems is an asset in the detection of changes which occur over time.

Given the great amounts of information collected, the evaluation of the data is usually performed with the aid of modern computer facilities.

Using information provided by the LANDSAT-1 satellite, formerly known as ERTS-1, research was performed to investigate the feasibility of remotely detecting Iowa's natural resources and features. The main concern of this research was a land use inventory over relatively small areas of the state--county size and smaller--to assess forest and crop land acreage estimates and, in the case of major crops, to assess yield forecasts. The potential of photographs taken aboard the Skylab spacecraft for general soil classification purposes was also investigated.

REVIEW OF LITERATURE

Remote sensing involves the collection of data by systems which are not in direct contact with the objects or phenomena under investigation. As used here, the collection of data consists of measurements performed on selected portions of the electromagnetic spectrum.

Stone (1974) considers unfortunate the fact that "remotely sensed data interpretation" has not been introduced instead of the term "remote sensing" because the realm of these activities goes much beyond the mere collection of data.

Human eyes are examples of remote sensors with great capabilities. When perceived by them, electromagnetic energy reflected from an object is converted into a nerve impulse which the brain records as an image. Human eyes perceive only the visible portion of the electromagnetic spectrum. Remote sensing systems have been developed to gather information using other portions of the electromagnetic spectrum. Images can then be produced which human beings can experience with their eyes. Modern remote sensing techniques constitute powerful means for the study of the terrestrial environment.

The interaction of electromagnetic energy with an object and its environment gives origin to spectral signatures which, when adequately measured and interpreted, can lead to identification.

The successful acquisition and interpretation of remote sensing data is crucially dependent upon knowledge concerning quantitative and qualitative variations of electromagnetic radiation measured by sensors.

A convenient way to deal with and to understand these interactions is to orderly follow the steps leading to the development of a remote sensing system, starting with the source of the energy involved in the system, following its path through the earth's atmosphere, the alterations it experiences when impinging upon surface features, and its detection and measurement by the sensor. A last step has to be concerned with the characteristics of the gathered information, how it is processed, interpreted, and used.

Nature and Sources of the Energy Measured by Remote Sensing Systems

Electromagnetic radiation, as defined by classical theory, is energy propagated through space or through material media as a transverse wave motion advancing in the form of periodic fluctuations of the strengths of electric and magnetic fields occurring at right angles to the direction of propagation of the energy (Huschke, 1959). The length of the wave (λ) (distance from wave crest to the next), its frequency (f) (number of wave crests passing a given point in a specified period of time), and its velocity (v) (speed at which the wave crests advance) define the character of waves in the electromagnetic spectrum. Wave velocity is a constant, the speed of light, throughout the entire electromagnetic spectrum. A reciprocal relationship exists between wave frequency and wavelength, that is, $v = \lambda f$.

The ordered array of all known electromagnetic radiations is referred to as the electromagnetic spectrum of energy. This spectrum extends over a wide range of wavelengths and it is conventionally divided in regions or wavebands. Table 1 gives details about portions of the electromag-

Table 1. Wavelength ranges of operation for remote sensors (from Holter, 1970)

Spectral region	Band	Wavelength	Common applicable imaging sensors
Ultraviolet	Vacuum UV	0.004 to 0.100 μ 0.100 to 0.280 μ	These wavelengths do not penetrate the Earth's atmosphere significantly to be used for agricultural remote sensing
	Intermediate UV	0.280 to 0.315 μ 0.315 to 0.380 μ	Photographic film; quartz lenses; scanner with photomultiplier detectors; image-converter tubes
Visible		0.380 to 0.780 μ	Photographic film; scanners with photomultiplier detectors; television
Infrared	Near IR (Reflective IR)	0.780 to 3 μ	Photographic film to approximately 1 μ; scanners with infrared detectors; various image tubes
	Intermediate IR (Emmissive IR) Far IR	3 to 8 μ 8 μ to 1 mm	Scanners with infrared detectors; various image tubes (not very satisfactory)
Microwave	Passive Active UHF Active SHF	1 mm to 1 cm 1 to 10 cm 10 cm to 1 m	Scanning antennas with radio frequency receivers

netic spectrum presently used in remote sensing activities.

Remote sensing systems are classified as active or passive according to the origin of the energy being detected. Active systems are those in which the sensing device sends energy to the object under study and then measures the portion of that energy reflected back by the object. These systems are beyond the scope of this research.

Radiation emitted by the sun or terrestrial objects is the basic source of energy detected and measured by passive systems. All objects having temperatures above absolute zero emit electromagnetic energy. The quantity and quality of the electromagnetic energy is dependent on temperature and physical characteristics. A special case, of high theoretical significance, is one in which the intensities of the emitted radiation are considered to be exclusive functions of the temperature of the object and reference is made to the so-called black-bodies.

The amount and quality of solar radiation reaching a horizontal unit of the earth's surface depends upon 1) the intensity and spectral characteristics of the source of energy, 2) the angle of incidence of the rays which is determined by the sun's astronomical position, and 3) the transparency of the atmosphere.

When intercepted by an object, the solar radiation can be absorbed, transmitted, diffused, scattered, and reflected in particular ways according to the physical properties of the object. All of these processes take place when sun rays pass through the earth's atmosphere. Absorption of radiation by gases in the atmosphere is highly selective, in terms of wavelength, and may depend on pressure and temperature. Radiation scattering by molecules and dust reduces the amount of energy reaching the earth's surface in the visible region of the spectrum. Ultraviolet radiation is absorbed by oxygen and ozone while infrared radiation is selectively absorbed by carbon dioxide and water vapor. Only wavelengths which are highly transmitted through the atmosphere are apt to be used for remote sensing purposes. The solar radiation being reflected by ground features is mostly visible and near infrared. It is estimated that some 47% of an assumed 100% of solar energy arriving at the top of the earth's atmosphere reaches the surface of the earth. This absorbed energy is then emitted as thermal energy (Barrett, 1974).

Reflected and emitted radiation being sensed at some height over the earth's surface is also affected by a similar range of factors, depending on atmospheric pathlength. The apparent radiance of area A as measured by a sensor aboard a spacecraft is given by the following expression (Musick et al., 1973):

$$I_A = (I_{Sun} + I_{Sky})\rho_A \tau I_{up}$$

where:

I_{Sun} = direct solar radiation incident on the area

I_{Sky} = diffuse sky radiation incident on the area

ρ_A = reflectance of area A

τ = transmittance of the atmosphere along the path from the area to the sensor

I_{up} = radiation scattered upwards by the atmosphere over the area

All of the above terms are wavelength-dependent, but the subscript λ has been omitted for clarity. Figure 1 shows a schematic model of the atmospheric effects.

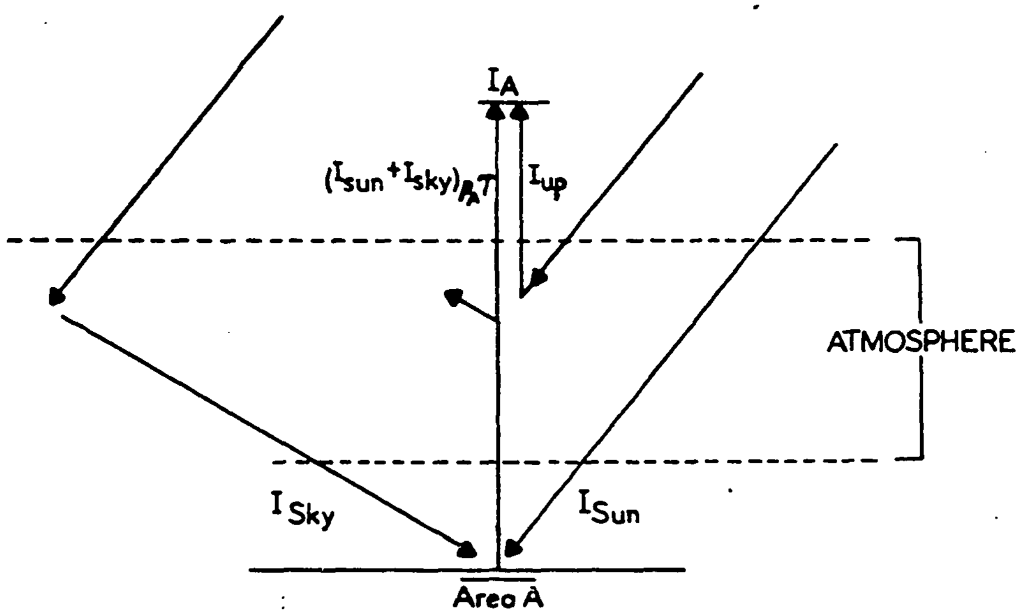

Figure 1. Atmospheric Effect Model (from Musick et al., 1973)

Basic Interactions Between Energy and Matter

Objects interact with each other in complex ways with respect to the energy they receive and emit. Thus, besides object temperature, important properties to be considered are object emittance, transmittance, and reflectance, and the character of the energy coming to them from the sun and surrounding environments. These properties of the object are, in general, functions of its material absorption coefficient, its bulk configuration or shape, the aspect at which the object is viewed, and its surface structure (Holter, 1970).

Further complexity arises if these properties change with passing time. This is especially so when dealing with living organisms. They progress through different stages of growth and development bringing changes in their physical appearance and, in some cases, in their material composition. Even seemingly unchanging nonliving objects can be immediately altered in their spectral properties by something so simple as a film of water as provided by a rainfall or dew, for instance. Thus, changes in spectral characteristics are common in nature.

Remote sensing work dedicated to crop identification is dependent upon such factors as leaf morphology and internal structure, chemical composition and physiological status, canopy geometry, stage of growth or development, soil site characteristics, cultural practices, and weather conditions (Bauer, 1975).

The energy reflected from plant leaves varies with the quality of the incoming radiation. Spectral reflectance of most chlorophyll-containing vegetal surfaces is similar (Figure 2).

Healthy, fully developed green leaves show minimum reflectance in the visible region of the spectrum and maximum reflectance in the near infrared. The peak in the visible region near 0.55 micron accounts for the green color of plants which human eyes perceive. It is characteristic to have a sharp increase in reflectance near 0.7 micron and a decrease near 1.5 microns. In the near infrared, reflectance is also high but decreases gradually to a low level at 2.5 microns.

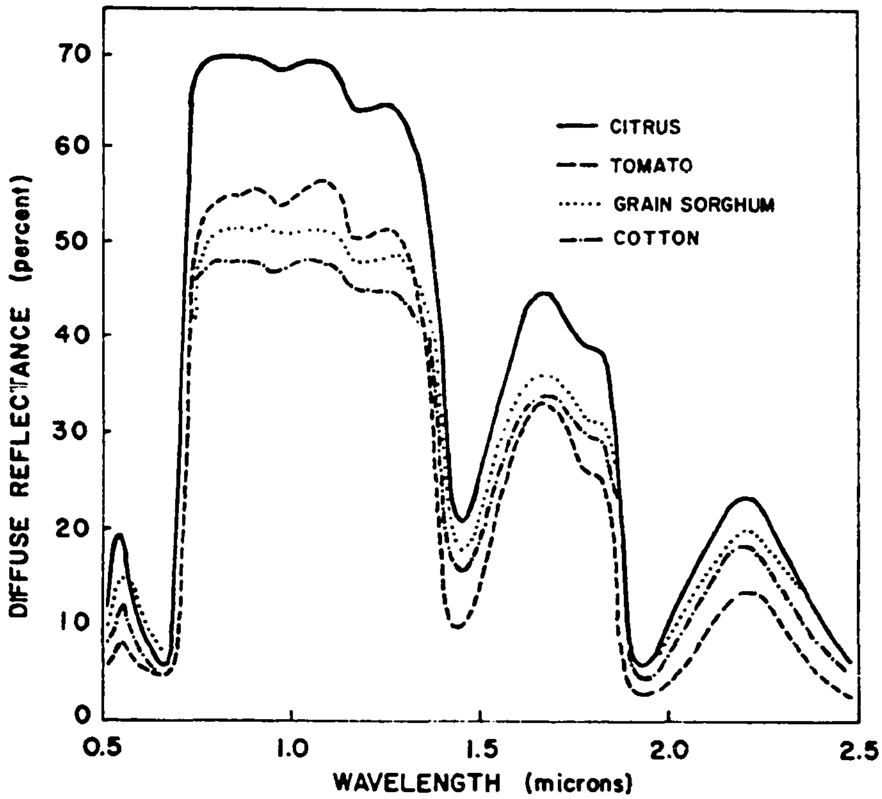

Figure 2. Light reflectance from leaves of four agricultural crops (from Myers, 1970)

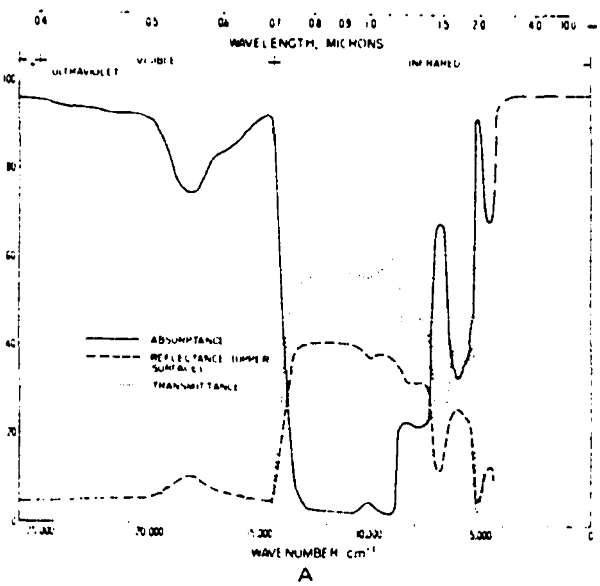

Figure 3. Spectral reflectance, transmittance, and absorptance for <u>Populus deltoides</u> (from Gates, 1970)

The reflectance of leaves is attributed to their internal structure. Internal reflectance within leaves occurs by critical reflectance at the cell-air cavity interfaces in the spongy mesophyll tissue of leaves (Gates, 1970). While this theory seems to hold in relation to visible reflectance, it does not seem to account for the observed infrared reflectance. Sinclair _et al_. (1973) presented the hypothesis that visible and infrared reflectance is due to the diffuse characteristics of cell walls. They concluded that diffuse as well as specular reflectance must be considered when dealing with the pathway of light through leaves.

Energy which is not reflected or transmitted is absorbed. Incident energy which is transmitted through leaves presents a spectrum which closely resembles the reflectance spectrum, but generally at a lower level (Figure 3). Absorption by leaf pigments, primarily by chlorophylls, although carotenoids, xanthophylls, and anthocyanins also have an effect (Gates _et al_., 1965), is high in the visible region; and thus less energy is available to be reflected and transmitted, resulting in the above mentioned low values of the respective spectrums. The absorptance is again high in the far infrared due to liquid water absorption (Gates, 1970; Allen and Richardson, 1968; Gausman _et al_., 1970). Chlorophyll pigments are completely transparent to infrared radiation (Knipling, 1970).

Green leaves go through changes in spectral properties both early and late in the growing season as shown in Figure 4A. Those early changes are attributed to modifications in leaf surface appearance, internal structure, water, and pigment contents among other possible

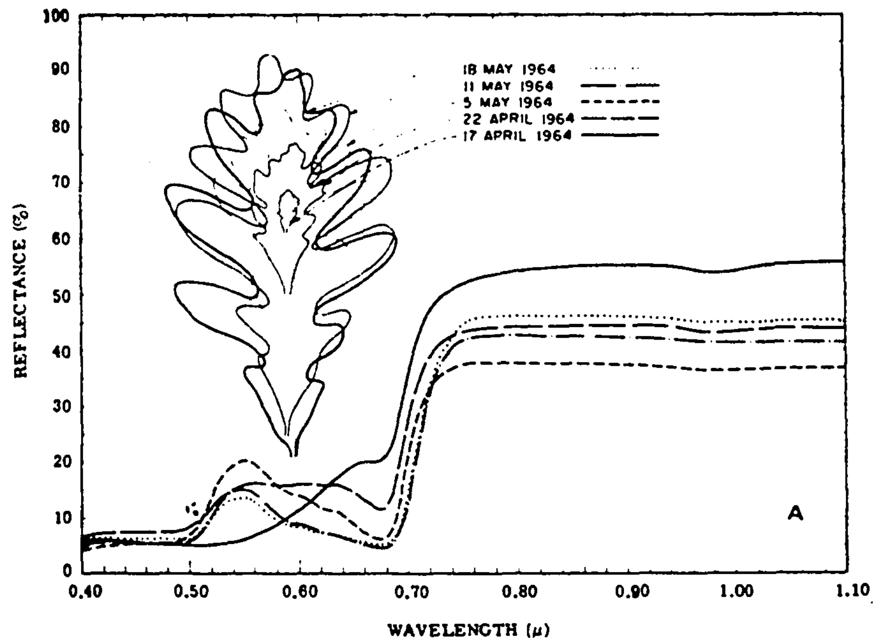

Figure 4A. Changes in spectral reflectance throughout growing season in Quercus alba (April-May) (from Gates, 1970)

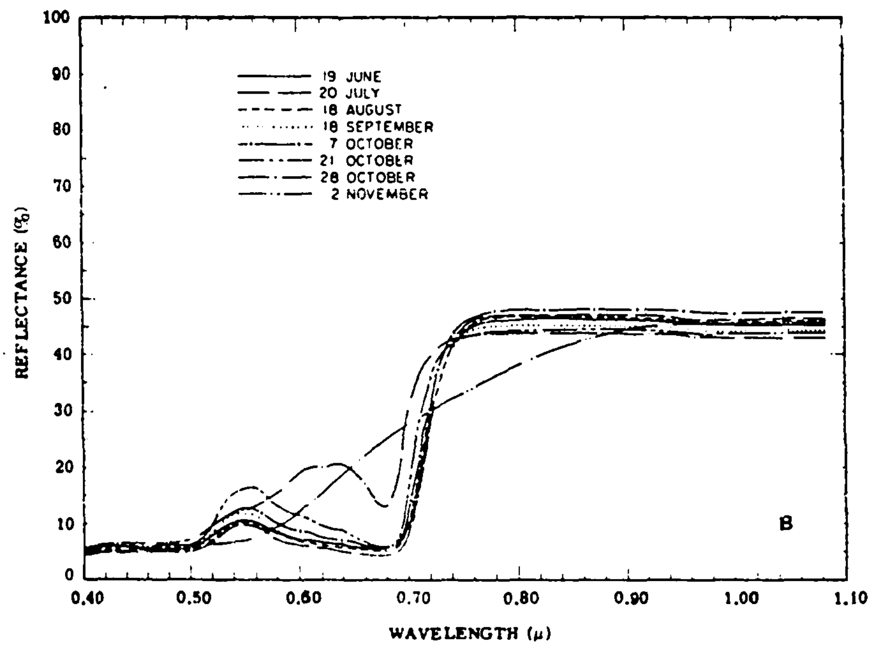

Figure 4B. Changes in spectral reflectance throughout growing season in Quercus alba (June-November) (from Gates, 1970) factors occurring through the life cycle of the leaf. The spectral characteristics of fully developed leaves remain unchanged until alterations in soil chemistry, climatic conditions, or pathogenic activity bring modifications in leaf chemistry, especially in relation to pigment and water contents (Gates, 1970).

Maturation and senescence are physiological conditions which commonly affect leaf reflectance. Figure 4B shows the changes in spectral reflectance occurring at the end of the growing cycle. The spectral reflectance remains stable until leaf senescence. When pigment change from chlorophyll to anthocyanins occurs, increased reflectance at all visible wavelengths is observed (curve dated October 28 in Figure 4B). Two days later, absorption in the blue region of the visible band and yellow reflectance were very much enhanced. The reduced reflectance in the near infrared is attributed by Gates (1970) to further destruction of pigments, but a deterioration of the leaf internal structure seems a more likely reason for that reduction at senescence. The reflectance in the far infrared probably increased somewhat due to less water absorbing radiation.

While basic to understanding the reflectivity of a crop canopy, the reflectance properties of single leaves cannot be applied directly to remote sensing investigations without considering many more interacting factors which bring, both quantitative and qualitative, differences in the two types of spectra (Knipling, 1970; Kanemasu, 1974).

The reflectance of single leaves is somewhat higher than that of a crop canopy. In the latter, part of the radiation is trapped by multiple reflection. There is a progressive decrease in available energy from the top of the canopy downward, with that attenuation being different for visible and near infrared regions of the spectrum (Allen and Brown, 1965; Kumura, 1969; Scott et al., 1968). Allen and Brown have shown also that attenuation within a plant canopy depends upon sun angle.

Differences in the proportion of reflected, visible, and infrared radiation have been observed between single leaves and crops. A relatively smaller reduction in infrared reflectance by crops than by individual leaves has been observed. Incident infrared energy transmitted through the uppermost leaves is reflected from lower leaves and retransmitted up through the upper leaves enhancing their reflectances (Knipling, 1970).

The ratio between infrared and visible reflection found by Scott et al. (1968) for crops was about double that reported by several authors for single leaves. For example, the ratio of the reflection at 0.80 micron to that at 0.55 micron is usually about three to one in leaves (Billings and Morris, 1951; Gates et al., 1965; Howard, 1966), while the corresponding ratio for vegetation canopies studied by Scott et al. was about six to one. Howard determined the spectral properties of a stack of up to eight eucalyptus leaves. He found that while there were only small changes in the reflection of visible radiation, the reflection of infrared radiation continued to increase from 50% for one leaf up to 80% for an eight-leaf stack. He concluded that, if a canopy acts like a stack of leaves, it implies that the deeper and more leafy a canopy, the higher should be its infrared reflection relative to visible radiation. Similar results were reported for stacked cotton leaves by Myers (1970) (Figure 5). The lack of significant differences in reflectance in the visible wavelengths from any combination of stacked leaves indicates that reflectance of visible light from leaf surfaces comes from the topmost exposed leaves.

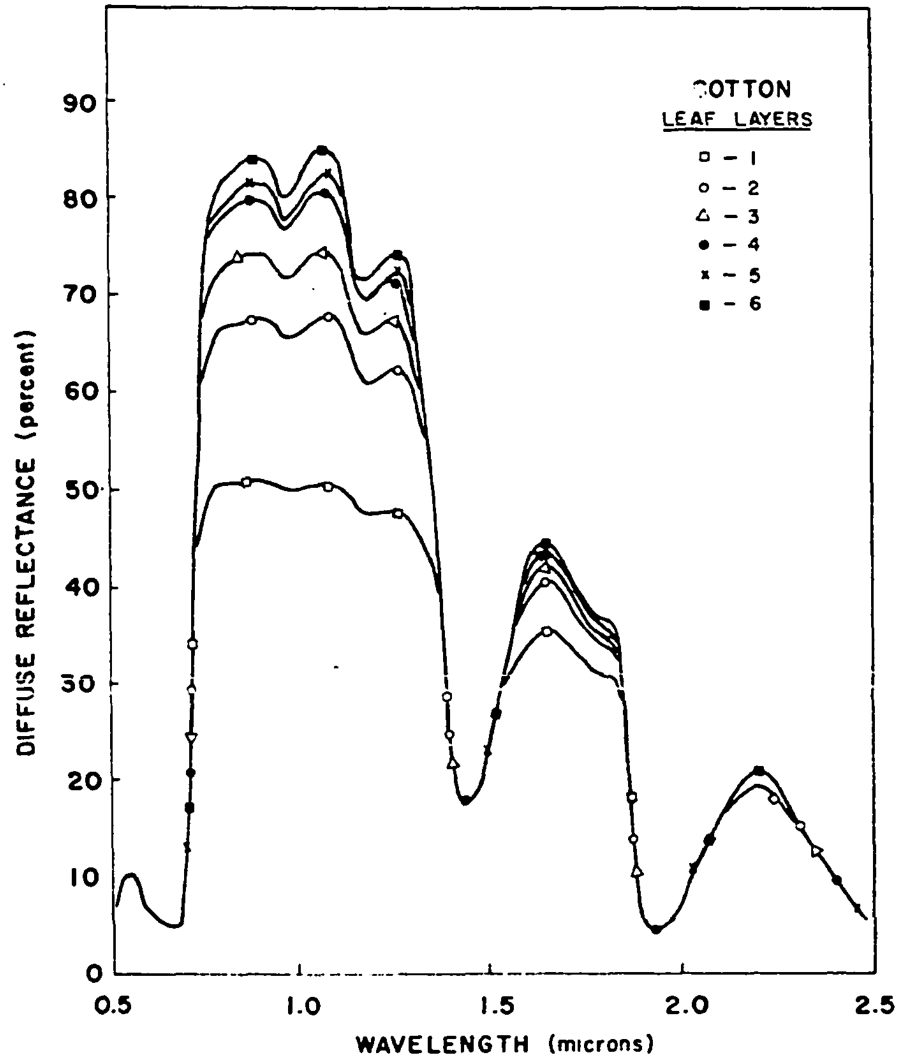

Figure 5. Diffuse reflectance from combinations of cotton leaves stacked on one another, up to six deep (from Myers, 1970)

A known cause of variation in reflectance from a given canopy is the leaf area index (LAI) of the canopy (LAI = ratio of leaf area to soil area). Immediately after emergence, crop LAI is low and soil reflectance predominates. As plants grow throughout the season, LAI increases and so does canopy reflectance up to maximum LAI and reflectance values when a full crop canopy has developed.

Background reflectance may be quite important in affecting canopy reflectance, especially at low LAI values. Most canopies are mixtures of different components besides leaves. Background soil reflectance, amount of leaf litter, shadow, and other plant parts are usually present. This is especially true for forest canopies. A deciduous forest in winter, presenting a surface of bark and ground leaf litter cover to a spectral scanner will give sharp differences in reflectance when compared to a coniferous forest in that season.

In addition to the effects due to degree of shadowing by plants, the reflectance of a soil surface depends upon its coloration, texture, moisture content, mineral composition, and angle of incoming solar radiation.

The degree of health of the components of the canopy also influences reflectance. Numerous remote sensing investigations have dealt with reflectance characteristics of nutrient-deficient crops, crops with soil salinity problems, and moisture-stressed crops.

Data Acquisition, Processing, and Interpretation

The sensors being presently used for detection of electromagnetic energy emitted and/or reflected by surface features can be divided in photographic and nonphotographic devices. These sensors are usually operated from airplane or spacecraft platforms.

Aerial photography is a relatively old remote sensing device. Its usefulness has not been diminished by the development of modern ones. Rather it is more a matter of reciprocally fruitful cooperation than that of competition. Because aerial photography is relatively well known, technical details will not be discussed here. Aerial photographic techniques have superior spatial resolution capabilities over radiometric scanners. These techniques are low in cost and operationally simple when compared to the complicated electronic equipment used in scanners, and they provide considerable information. Delays caused by film return to earth for processing are a disadvantage though, and its use is confined by present technology to the visible and near infrared regions of the electromagnetic spectrum (Heller, 1970).

Nonphotographic sensors operate in portions of the electromagnetic spectrum ranging from the microwave to the ultraviolet region. Included here are microwave devices and scanners. Infrared microwave sensors operate under both day and night conditions in the wavelength region from 0.1 mm to 3 cm. The infrared portion of the electromagnetic spectrum grades imperceptibly into the spectral region known as microwave. At microwavelengths, self-emitted radiation is much less than in the infrared. Highest sensitivities and lowest internal moise powers are required of the receiving devices (Holter, 1970). The name microwave is somewhat of a misnomer. Microwaves are small when compared to radio or television waves, but they are extremely long when compared to visible wavelengths. Microwaves are the longest wavelengths normally used in remote sensing (Holz, 1973).

Microwave radiometers are out of the scope of this work and will not be further considered.

Scanners, known as multispectral scanners, when capable of detecting several wavebands of a given scene at the same time, operate in the optical portions of the electromagnetic spectrum from 0.3 to 14.0 microns. The data, collected in electrical form, is transmitted in near real time to surface receiving stations. They possess higher spectral resolution than aerial photographs because detections are made in narrower bands within the spectrum.

The sensor consists of a motor-driven scanning mirror which receives the energy reflected or emitted from a small area of the earth's surface. This detected energy then passes through appropriate optics. In the case of visible radiation, it is directed through a prism which disperses the energy into respective regions of the electromagnetic spectrum. Radiometric detectors receive the energy from the prism and measure the energy (volts) in specific wavelength regions. These measurements are amplified and recorded on magnetic tape or transmitted to the ground. The infrared portion of the spectrum is dispersed by grating devices (Landgrebe, 1972).

At a given instant, the instrument is receiving and measuring energy integrated from a single portion of a scene (resolution or picture element -"pixel"-) as determined by the instantaneous field of view of the scanner which is a function of the configuration of the instrument and the altitude of the platform. A single data set contains all the information collected from a scene pertaining to that resolution element. Figure 6 depicts an idealized data recording sequence from four wavelength

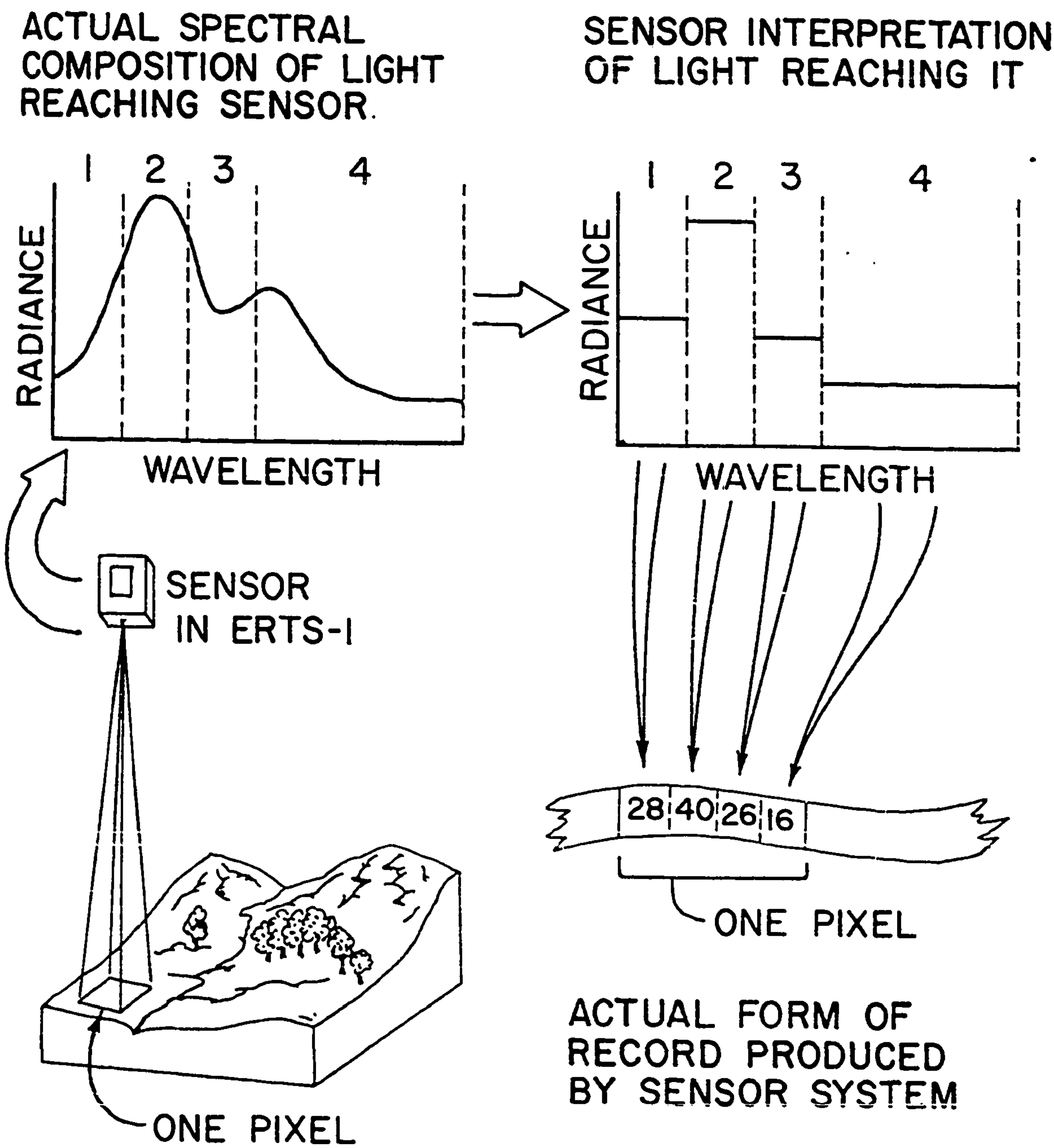

Figure 6. Data recording sequence in satellite sensor system (from Williamson and Grabau, 1974)

bands. The "real" reflectance spectrum (top left) is generalized into a histogram (top right).

As the platform which carries the sensor passes over an area, the mirror scans the ground surface in successive strips or scanlines at right angles to the direction of platform motion. The forward movement of the platform brings successive strips of ground into the field of view of the sensor. Successive scans in a properly functioning system are contiguous or slightly overlapping with neighboring scanlines. A unique pattern of radiometric measurements yielded by a given object is known as the spectral signature of the object.

The launching of the first Earth Resources Technology Satellite (ERTS-1) by the National Aeronautics and Space Administration (NASA) on July 23, 1972, marked the initiation of routine remote sensing data acquisition with multispectral scanners. That satellite, designed specifically to monitor and investigate the natural resources on Earth, was later renamed LANDSAT-1. For similar purposes, a second satellite, LANDSAT-2, was launched on January 22, 1975.

The following technical details about LANDSAT-1, unless otherwise indicated, were summarized from papers by Boeckel (1974), Steiner (1971), Rifman (1973), and NASA (1971).

LANDSAT-1 weighs approximately one ton. It completes an orbit around the Earth once every 103 minutes at an altitude of about 832 km. The orbital path progresses approximately 159 km westward each day above the rotating Earth, such that every 18 days the entire Earth is covered by the satellite. It crosses the equator in a north-south direction at about 0942 local time. Successive orbits are separated by about 2870 km at the equator, thus there is no sidelap between successive satellite passes, but these large gaps are filled in successively during an 18-day period and on the 19th day the satellite duplicates the passes at the beginning of the period.

Its orbit is sun synchronous. That is, the local time along satellite path is a constant, so it passes over the same spot on Earth at approximately the same hour every 18 days. This insures a minimization of variation in solar illumination. The solar altitude varies with latitude and season of the year. The relatively early daytime for the satellite passes seems to have been chosen with a particular view of the mapping of land forms. These obviously stand out more clearly with an increased shadow effect at a relatively low solar altitude.

LANDSAT-1 was initially equipped with two types of sensing systems; however, early technical difficulties required one system, the Return Beam Vidicon or RBV, to be shut down. The remaining system is a multispectral scanner (MSS) which senses solar energy reflected from the earth's surface in four wavelength regions:

Band 4 (MSS 4): 0.5 - 0.6 μ

Band 5 (MSS 5): 0.6 - 0.7 μ

Band 6 (MSS 6): 0.7 - 0.8 μ

Band 7 (MSS 7): 0.8 - 1.1 μ

Bands 4, 5, and 6 use photomultiplier tubes as detectors. Band 7 uses silicon photodiodes.

Shown in Figure 7 is a schematic diagram of the multispectral sensor carried aboard LANDSAT-1. The four band sensor scans 185 km wide cross-track swaths by means of an oscillating planar mirror which images all four bands simultaneously. The four bands are thus inherently spatially registered. Six detectors are assigned to each spectral band, so that six scanlines are recorded simultaneously. The instantaneous field of view of a single sensor element is approximately 80 m square on the ground from the nominal satellite altitude.

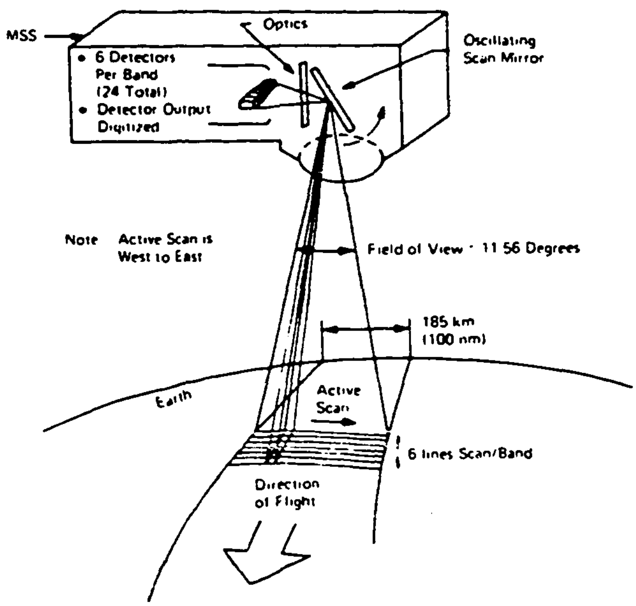

Figure 7. Multispectral Scanner Sensor (from Bernstein, 1974)

Each MSS bulk image represents 2340 individual active scanlines, obtained during approximately 28.6 sec of "picture time". The center/center cross-track separation of adjacent field of views is about 57 m so that there is nearly 30% overlap between adjacent samples (Ellefsen et al., 1973). Thus, the sampling interval along a scanline is smaller than the sampling interval between scanlines. In other words, there are more picture elements along a kilometer on the surface of the Earth parallel to a scanline (approximate east-west direction) than a kilometer normal to a scanline (approximate north-south direction). The nominal 80 m square dimension of a resolution element finally results in a dimension approximately 79 by 57 m, that is, a pixel covering 0.45 hectare or 1.1 acre. Successive scanlines are slightly shifted to each other owing to the earth's rotation in relation to the satellite velocity.

The MSS data are recorded continuously in the along-track direction. However, MSS imagery is processed to frames 185 km by 185 km.

No aerial photosystem or film return space system provides imagery as near orthogonal as that of LANDSAT. The four wavebands recorded by LANDSAT-1 can be combined to provide a response optimized for particular scenes or for objects of sufficient size. Film cameras can record up to three bands on one film (color or "color infrared"), but altering the combination for a particular scene or object is complex and imprecise (Colvocoresses, 1973).

There are two types of constraints imposed on the remote sensing operations: 1) internal, i.e., payload or other technical limitations; 2) external, i.e., sun angle and cloud cover. The internal limitations in the case of LANDSAT-1 are dictated by power availability, tape recorder storage capacity, and ground communication link duration. The power conditions are such that the instruments can be operated for 20 minutes each orbit. The capacity of the tape unit is 30 minutes of recording, and the spacecraft is within the range of the U.S. ground stations for an average of 208 minutes per day. It is estimated that it takes about 45 scenes to cover the continental U.S. Each scene consists of four MSS images which can be transmitted in real time within about 18 minutes.

The theoretical capability of LANDSAT for sequential seasonal coverages may be hampered seriously by cloud cover in many parts of the world. Steiner (1971) has calculated the probability of successfully covering an area as a function of average percent cloud cover and number of satellite passes.

The geometry of the images produced by the sensors aboard LANDSAT-1 is influenced by factors categorized by Steiner as sensor-related (i.e., lens distortion), platform-related (satellite position and orientation during radiation measurements, causing changes primarily in platform altitude), and earth-related (i.e., earth's atmosphere, curvature, and rotation). Figure 8 summarizes all of this by showing an image error source sequence. All errors are nonadditive. Some are systematic in one or another direction, whereas others are directionally random. Proper geometrical rectification can reduce the overall errors to small amounts. NASA applies no less than fourteen geometric corrections to the MSS imagery.

LANDSAT-1 data are processed into either photographic products or computer compatible digital tapes (CCT). Images of two types with different degrees of accuracy are produced by the National Data Processing Facility at NASA/Goddard: system-corrected images and precision (scene)-processed images. The system-corrected images are corrected for the

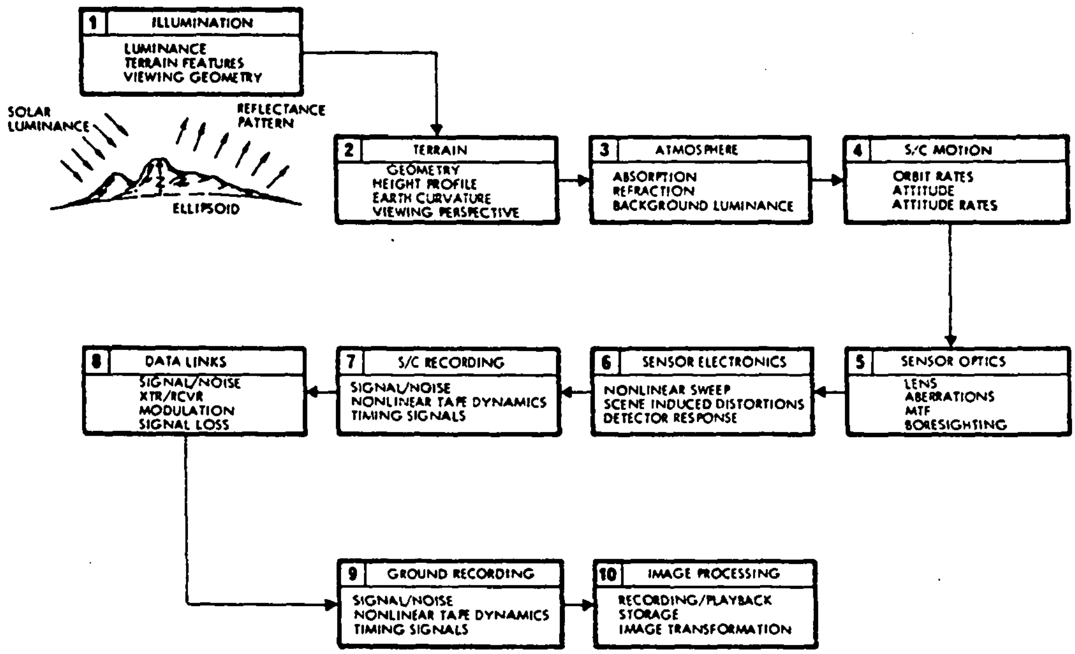

Figure 8. Image Error Source Sequence (from Taber, 1974)

major distortions introduced by spacecraft orientation, sensor characteristics, and the earth's rotation. Precision-processed images include additional adjustments based on a number of in-scene ground-control points in each frame. The National Aeronautics and Space Administration (NASA) provides transparencies and/or prints at 1:3,369,000 and 1:1,000,000 scale to the U.S. Interior Department through the EROS Data Center at Sioux Falls, South Dakota, which sells to LANDSAT-1 data users.

The bulk digital computer-compatible tape data are not corrected for any of these distortions. Four tapes depict a scene 185 km square, each tape giving information on one strip approximately 46 km wide for each MSS band.

Bulk data are preferred to precision CCT data for recognition processing because, in the latter, the radiometric accuracy of the data is degraded by re-scanning. Therefore, when displayed on a line-printer map, substantial distortions are evident in bulk CCT data. Square sections are displayed as parallelograms, and other distortions are present which further increase the difficulty of assigning resolution elements to specific ground areas.

May (1974) reported a reduction in tape costs and storage facilities when the four scene depicting tapes were compressed to fill less than one reel of magnetic tape using a technique he developed.

Any image is a two-dimensional projection of a three dimensional surface. Thus, in addition to the reflectance of a given material, a depth information is encoded (in an unknown fashion) in every value of the image.

The images acquired by multispectral scanners can be analyzed making use of common photointerpretation techniques, even though they are not true photographs. They can also be digitized and like the data provided by the CCT be subject to modern techniques of computer assisted interpretation.

Classical, manual, photointerpretation of LANDSAT-1 imagery is relatively simple and inexpensive; furthermore, newly developed techniques have expanded its capabilities. For instance, different colors can be added to an image--singly or in combination--to facilitate the identification of features, the image can be displayed on television screens, and computers can assist in the interpretation. Investigations performed using classical techniques were frequently reported in the literature, especially immediately after LANDSAT-1 data became available. Some were referenced by Breckenridge _et al_. (1973), Brown _et al_. (1973), Carlson and Fenton (1975), Jayroe _et al_. (1974), and Williams _et al_. (1973).

Numerical analyses facilitate large scale surveys covering large areas practically out of reach of manual interpretation procedures; only computers can handle the vast amounts of data which are needed.

Landgrebe (1972) clearly illustrates the expanded usefulness of spectral information gathered by the sensors when advantage is taken of its spatial and temporal variations. Spectral information obtained on different days from the same ground scene sometimes provides means for discerning among features otherwise presenting no differential response within a single set of measurements. For example, two species yielding similar spectral responses for some period after planting would be differentiated if, in addition to the plants of the two crops having a slightly different spectral response, crop canopy geometries and growing cycles are different. This temporal information is made available by selecting the time at which differences among features are optimized. This is not always feasible because, if using LANDSAT-1 data, the time elapsed between successive satellite passes could miss the best time for finding spectral differences or cloud formations may interfere with data collection.

Another dimension which sometimes is added to spectral information is a spatial one. For instance, by plotting on different axes, responses obtained at two different MSS bands, a two-dimensional feature space is obtained which can be numerically analyzed to differentiate among features. The information can also be plotted on more complex, multi-dimensional graphs, though numerical analysis will present increased difficulties. Temporal information can be analyzed in a similar way. In the simplest case, two or more features whose spectral responses are different will lie in different portions of the two-dimensional space. The features are then said to have unique spectral signatures. However, all successive measurements taken by the scanner at a given wavelength from a scene, say one encompassing field crops of a given species, usually do not yield the same spectral response, since most likely they will not have been planted the same day and under identical circumstances with respect to soil preparation, moisture conditions, etc. At the end of the numerical analysis, each one of the separable features will define a class relative to the other classes identified in the same process.

Another way of considering the spatial features of the response is by obtaining its Fourier spectrum (Gramenopoulos, 1973; Hornung and Smith, 1973). The Fraunhofer diffraction pattern of an image is related to its two-dimensional Fourier transform. If a transparency is introduced into the front focal plane of a lens and illuminated by a coherent plane parallel beam, the lens will form an image at its back focal plane which is the diffraction pattern of the image. Physically the diffraction pattern contains spatial features which are possibly unique to a given image.

Considering the great number of variables acting upon the responses obtained from a feature at a given time, those responses are not related to measurements performed at other times. They come from relative, not absolute values. As Landgrebe (1972) put it, no "bank" of signatures is possible without absolute measurements. There have been some attempts to obtain absolute values (Rogers et al., 1974; Goetz and Billingsley, 1973).

How to assign every measurement to a given class whichever the dimensions used--spectral, temporal, spatial--has been and still is the subject of a great number of procedures by which researchers try to accomplish this. There are simple ones by which so-called training samples are obtained by selecting and locating, within the data to be analyzed, specific examples of each of the classes to be utilized. Information about the spectral characteristics of the training samples is usually provided by ground observations at the selected sites and/or by low-altitude aircraft flights usually taking aerial photographs. This kind of information is commonly referred in the literature as ground truth data. The data elements that are used in the classification algorithm are obtained through human input, that is, the classification is supervised. Data analyses performed using supervised classifications have been reported, among others, by Rehder (1973), Morain and Williams (1974), Draeger et al. (1974), Heydt and McNair (1973), and Poulton and Welch (1973).

More complex, computer aided procedures of data analysis were developed to automatically obtain training samples. These are called nonsupervised classifiers. The aim is to replace subjective methods of evaluation and interpretation by objective, automatic procedures applicable to handling a great mass of data. Groups of spectral responses are formed according to the degree of similarity among them, which has to be greater than their degree of similarity with respect to the remaining groups. These procedures, known as clustering techniques, can be used to divide the data set into an arbitrary number of classes or clusters. Clustering algorithms were used, among others, by Gramenopoulos (1974), Gustafson (1973), Kan et al. (1973), Ellefsen (1973), Jayroe et al. (1974), and Hoffer and Staff (1974). Some of the specific clustering techniques are summarized by Sokal and Sneath (1963) and Sokal (1966).

Initially assumed in this procedure is the possibility of obtaining the clusters; final classification provides the check for this hypothesis. However, there remains to be determined that all the points assigned to a single cluster in fact belong to the same class. The scene analyzed can be displayed with spectral responses grouped according to class and also each cluster can be statistically analyzed to locate decision boundaries. The procedures are even more valuable when boundaries among classes are not obvious to the human operator (Landgrebe, 1972). The term pattern recognition refers to the development of techniques and equipment for the automatic recognition of selected patterns within numeric data sets.

Many researchers have felt compelled to modify LANDSAT-1 data to make possible or to facilitate their classification procedures. Hoffer and Staff (1974) developed a procedure to rotate, deskew, and geometrically scale LANDSAT-1 data results into 1:24,000 scale printouts that can be directly overlayed on U.S. Geological Survey topographic maps. Malila and Nalepka (1974) used an empirical transformation to produce rotations in LANDSAT-1 data to account for its nonpolar orbit and the difference in orientation between earth and satellite coordinates correcting also for effects of the earth's rotation and other sources of distortion and error. They also developed a technique to overcome the limited spatial resolution of scanners like that of LANDSAT-1. Peet _et al_. (1974) used so-called affine transformations to relate aerial photographs or topographic maps to computer compatible tapes. Emert and McGillem (1973) also used affine transformations. Malila _et al_. (1973) developed a computer-aided procedure to correlate coordinates from topographic maps and/or aerial photographs with LANDSAT-1 coordinates.

Williamson and Grabau (1974) subdivided each LANDSAT-1 picture element into three picture elements to obtain a transparent overlay fitting over a base map. Pirie (1974) used a multiple regression surface fitting technique to eliminate scattering in the data values (data smoothing).

When classifications are based on multidate (temporal) imagery, usually some way of data registration has to be devised. Image registration is a procedure to determine the spatial best fit between two or more images that overlap the same scene. Peet _et al_. (1974) used also affine transformations to register data sets. Weber (1973) and Yao (1973) developed several techniques for image registration. Erb (1974) indicated that accuracies in the range of 70-90%, obtained when using single data sets to identify crop types and forests, can be improved up to the 95% range using registered data sets.

Other researchers manipulate data to enhance image contrast allowing the interpreter or the computer to make decisions which otherwise may be beyond the capability of pattern recognition techniques or prohibitively costly (Goetz and Billingsley, 1974). Enhancements can be used as preprocessed data for classification purposes. A natural imagery enhancing occurs when snow covers a scene at measurement time. Interpretation of snow-covered satellite images made by Wobber and Martin (1973) indicated that a heavy "blanket" of snow (e.g., more than 9 inches) accentuates major structural geological features, while a light "dusting" (e.g., less than 1 inch) accentuates more subtle topographic expressions.

The method of ratioing or subtracting multispectral images can be viewed as a form of contrast enhancement. Wiegand et al. (1974) considered ratios of LANDSAT-1 bands MSS 5/MSS 7 and MSS 7-MSS 5 to be practical indicators of vegetative cover and density in addition to bands MSS 6 and MSS 7. Kanemasu (1974) suggested using the ratio MSS 4/MSS 5 during the growing season to detect wheat growth and disease. Yarger et al. (1974) found a strong sun angle dependence in all LANDSAT MSS bands which they suppressed by ratioing.

Results Obtained Analyzing Remote Sensing Data

Remotely sensed data are used in many agricultural and nonagricultural investigations. Possible applications for agricultural surveys are given in Table 2. The most promising uses until now are referred to crop identification and area estimation, crop condition assessment, yield forecasting and estimation, rangeland surveys, and soil mapping (Bauer, 1975).

Results on major crops identification reported on the literature usually approach or exceed the 90% accuracy level. Using positive transparencies, selected areas of all MSS bands were converted to digital

Table 2. Possible applications of remote sensing techniques for agricultural surveys (from Thaman, 1974)

A. Areas of general application:

agricultural land-use mapping	rural transportation network
agricultural land-use change	soil surveys
agricultural population distribution	water resource surveys
land-use potential	

B. Areas of specific applications:

1. Applicable to crop surveys:

crop identification	irrigation effectiveness
crop area estimation	drought prediction
crop vigor	weed concentrations
crop density	nematode infestations
crop maturity	insect infestations
growth rates	disease infestations
yield forecasting	location of disease-resistant species
actual yield	frost damage
planting dates	storm warning
harvesting dates	flood warning
soil fertility	fire surveillance
areas of fertilizer application	fire control
effects of fertilizers	damage assessment
soil toxicity	water availability
soil moisture	location of canals
excessive salinity	detection of heat in silos, etc.
water quality	
irrigation requirements	

2. Applicable to range surveys:

forage-species identification	soil fertility
delineation of forest types	soil moisture
condition of range	weed infestation
carrying capacity	insect infestations
forage yield	disease infestations
growth rates	wildlife inventory
times of seasonal change	effects of wildlife
development potential	rodent damage
location of water	fire surveillance
water quality	fire control
drought prediction	trafficability
extent of erosion	conditions of fences
identification of toxic species	

3. Applicable to livestock surveys:

cattle population	distribution of animals
sheep population	animal behavior
pig population	health of animals
poultry population	disease identification
age-sex distribution	types of farm buildings

form by Horton and Heilman (1973) to successfully distinguish between corn and soybeans in South Dakota.

Bauer and Cipra (1973) using a nonsupervised classifier were able to identify corn and soybeans in Illinois. They found their estimates to agree well with USDA estimates, particularly for corn.

Good recognition of corn and soybean crops, which have mature and uniform canopies when data were collected, was obtained by Safir et al. (1973) in Michigan. They also recognized accurately bare soils and forested areas. They found difficulty in classifying senescent vegetation which showed nonuniform distribution of dead and dying vegetation along with patches of more healthy vegetation.

Several crop types (rice, safflower, alfalfa, cotton, etc.) were successfully classified by Bizzell et al. (1973) in an area in the San Joaquin Valley, California.

Williams et al. (1973) classified winter wheat in Kansas. On a test sample of more than 22,000 hectares, 89% of the area was correctly classified as wheat or nonwheat using a single MSS 5 image acquired at planting time. The estimated wheat area was 99% of the actual area of wheat in the sample area.

Draeger et al. (1974) developed an integrated system utilizing both human and computer analysis of ground, aerial, and space imagery for regional crop acreage inventories. Their technique involves the delineation of LANDSAT images into relatively homogeneous strata by human interpreters, the point-by-point crop type classification of the area within each strata using a human-machine interactive system, and the collection of aerial and ground data to adjust and verify the classification results. This work was performed in San Joaquin County, California where the major crops include asparagus, corn, and alfalfa.

Crop species discrimination was performed by Erb (1974) in five states in which examples of the most important U.S. crops and practices were located and in a natural pine forest. He utilized conventional image interpretation and computer aided (spectral pattern recognition) analysis using both image products and CCT. He concluded that computer-aided analysis techniques perform as well or better than conventional image interpretation, but both techniques are useful for most surveys. He demonstrated the feasibility of large area crop and forest resource classification.

The detection and recognition of crop stresses using remote sensing techniques is a much more difficult task than crop species identification. Comparison between healthy and stressed vegetation is based on relatively small differences in spectral responses. Changes in leaf area and orientation and amount of ground cover may lead to identification of stress conditions through changes in scene reflectance and emittance.

Experiments performed in 1970 by Purdue University's Laboratory for Applications of Remote Sensing (LARS) showed that three degrees of corn crop infestations with leaf blight could be differentiated using either small-scale infrared aerial photography or multispectral scanner data (Bauer, 1975).

Satellite image interpretation supported by electronic color enhancement allowed Murtha (1974) to delineate three forest zones in Ontario, Canada, differently damaged by SO_2 fumes.

Pedgley (1974), using satellite imagery, located a 500 km square area of Saudi Arabia within which the Desert Locust bred. Also concerned with insect pests using remote sensing techniques were investigations reported by Coleman et al. (1973), Hall (1974), and Anderson et al. (1973).

Yield forecasting and estimation is linked to crop species identification and to proper assessment of variables which may lead to changes in potential yields. Variables such as crop density, healthiness, and degree of maturity may increase or depress yields. Also acting are weather conditions which by departing from average or normal values can equally alter yields.

Wiegand et al. (1974) investigated vegetation density as deduced from satellite information. They found that vegetation parameters (LAI, plant population, plant cover, and plant height) explain most of the variation in MSS 6 and MSS 7 responses. The correlation coefficient between LAI and MSS 6 responses was 0.82 for ten cotton fields investigated and 0.84 for a combination of three corn and ten sorghum fields. The correlation coefficient between LAI and MSS band 6 minus MSS band 5 was 0.89 for cotton fields and 0.77 for the corn and sorghum fields. The four plant parameters explained 87 to 93% of the variability in the MSS 6 responses and from 59 to 90% of the variations in bands 4 and 5. Plant population was found as useful as LAI for characterizing the corn and sorghum fields, and plant height was as good as LAI for characterizing cotton fields. This work provides procedures which can be applied to crop yield assessment using satellite data.

Morain and Williams (1974) applied a model for estimating wheat yields to aerial estimates for that crop derived from multidate LANDSAT-1 MSS 5 and MSS 7 imagery. Wheat fields were visually located and their acreage was estimated. The model, developed by Thompson (1969b) is based on rainfall and temperature departures from average values. The work was completed while the harvest was in progress. The results for a ten county area in southwest Kansas were within 3% of the preharvest estimates for the same area prepared by the USDA Reporting Service.

Aerial photographs have been widely used to differentiate soil association landscapes. Multispectral scanners bring spatial and temporal advantages and, thus, are used now for that purpose. These advantages include wide area coverage and their spectral and repetitive characteristics. Soil landscapes exhibit characteristic surface geometries, such as relative frequency of streams, and composition, such as percentage of bare soil areas and vegetation occupied areas. These can be recognized on satellite imagery.

Westin and Myers (1973) used LANDSAT-1 color composites of bands 4, 5, and 7 to identify soil associations in western South Dakota. Soil association boundaries were corrected and new soil associations were discovered. Baumgardner et al. (1973) used satellite imagery to map soil resources in Lynn County, Texas. They used CCT data with interactive machine processing to produce a general soil map. Mathews et al. (1973) prepared soil maps using MSS remote sensing and computerized pattern recognition techniques. Computer maps were found to be similar to detailed field maps prepared by conventional methods. The potential, as a tool for use in improving the speed and accuracy of field soil mapping, is obvious.

Draeger and Benson (1973) considered the feasibility of using remote sensing techniques in operational agricultural resource surveys. They concluded, to make that possible, "...increased consideration must be given to the development of data acquisition, analysis, and handling procedures which are specifically suited to large-scale, regional operations". According to them, "...procedures must be developed with the information requirements of prospective user agencies in mind, and investigations must be designed such that a quantitative basis is provided for objective cost-accuracy comparisons of alternative information-gathering and processing systems".

To demonstrate the utility of satellite observations, corn crops in Iowa were selected for a near real-time LANDSAT monitoring study (General Electric, 1976). Beginning in the 1976 growing season, the LANDSAT Agricultural Monitoring Program (LAMP) has established an "Alarm System" for corn in Iowa which utilizes satellite imagery in conjunction with weather data (air temperature, precipitation, growing degree units, and soil moisture) and field reports to monitor crop growth and development, identify anomalies, assess their impact, and adjust crop production forecasts.

MATERIALS AND METHODS

LANDSAT-1 and low-level imagery acquired over portions of Iowa in 1973 under National Aeronautics and Space Administration (NASA) Contract #NAS5-21839 by an interdisciplinary group of researchers constitute the basic data with which this investigation is concerned.

Bulk, computer-compatible tapes and corresponding photographic material (70 mm black and white positive transparencies) were acquired for the best cloud-free satellite images available during the 1973 crop-growing season for a scene in central Iowa. These images were collected by the LANDSAT-1 satellite on January 4, May 10, July 2, and August 26. Another source of data was photographic material (114 by 114 mm transparencies) obtained by the astronauts aboard the Skylab mission over a region in southwest Iowa.

Low-level photography provided under the NASA contract during May and August over portions of Boone County covering a two-section-wide strip was used as ground truth. These images encompassed Sections 7 to 18 in Colfax Township and Sections 10 to 15 in Worth Township. Available were 229 mm regular color and infrared positive transparencies and black and white 114 mm transparencies filtered to wavelength regions compatible with the LANDSAT-1 sensors and black and white transparencies representing the thermal infrared.

From previous analyses of LANDSAT-1 imagery, digital responses collected by the satellite on May 10 for MSS band 7 and on August 26 for MSS bands 5 and 7 were known to provide the best available images for crop and land-use recognition in central Iowa. These responses were visually registered taking advantage of major highway intersections which were visible in both May and August images. This provided approximate registration points. Thus, registered temporal, multispectral responses from an area, including the sections for which ground truth data were available, were compiled on a magnetic tape. This facilitated data handling and reduced the time and cost of computer operation. Each piece of information included on that tape consisted successively of digital responses obtained from each measured 80 m square ground surface area in May (band 7) and in August (bands 5 and 7), in that order. The January CCT's were not available at the preparation time of the working tape; therefore, a place was left blank on the tape at the beginning of each set of data for later inclusion. This was never done. The working tape was compiled by Mr. Harvey Terpstra.

The digital data stored on the working tape were rendered on line-printed, single-band computer outputs and visually analyzed to approximately establish the location of the 12-section Colfax township area from which low-level imagery was taken. These sections were also visited field by field to identify the crops present.

Enlargements were made from black and white 114 mm transparencies to estimate the dimensions of the fields in the 12-section area. Boundaries were drawn on paper and fields were cut and weighted assuming proportionality between weight and field areas.

A training site was established in Sections 10 and 11 to gain information about the digital responses of major crop types and land-uses.

The information acquired on the training site was used to develop several computer-implemented feature classification procedures. Two approaches were then followed for recognition purposes in the 12-section area. One approach consisted of instructing the computer to read each set of multispectral, temporal registered responses and, on the basis of pre-established cut-off responses, decide upon what feature was present on each picture element. This resulted in a line-printed output expected to resemble what the ground truth information showed was actually present on the scene. The total number of points considered to be members of a given class were counted to determine the area occupied by each feature. The information provided by the training site was further extrapolated to classify all of Boone County.

In order to compare the results obtained using this classification procedure with the ground-truth information, black and white enlargements of the MSS bands included on the working tape covering the 12-section area were manually divided into picture elements by imitating the path followed by the satellite at sensing time. A distorted ground truth was then obtained which corresponded to the classification computer output. Classification results were then compared, pixel by pixel, with the distorted ground truth and the degree of accuracy of the classification procedure was assessed.

In order to easily incorporate features visible on other LANDSAT-1 images, 70 mm black and white LANDSAT-1 photographic material was digitized at South Dakota State University's Remote Sensing Institute using their Signal Analysis and Dissemination Equipment (SADE System). Six data files were recorded in total on an unlabeled tape in a linear mode at 1024 data points across 57 mm distance. Imagery location and tape documentation are shown in Table 3. Two hundred and fifty-six gray tones were recorded on tape for each digitized imagery (data values ranged from 0 to 255).

Table 3. Location and recording characteristics of the digitized imagery created by SADE

Imagery		Tape documentation[a]		
Date	MSS band	Location file number	Number of bytes/record	Number of records
	(Skylab)	1[b]	800	650
January 4	7	2	700	575
May 10	7	3	750	600
July 2	7	4	500	500
August 26	5	5	650	600
August 26	7	6	650	600

[a]Fixed record format; record length and blocksize equal.

[b]File created at speed 1 of SADE; the remaining five files were created at speed 2 because of processing time limitations.

Only a portion of each transparency was digitized encompassing areas in central Iowa along the Des Moines River (files 2 to 6) and Mills County in southwest Iowa (file 1). Those portions digitized for central Iowa were of unequal size because the transparencies covered slightly different ground areas due to satellite orbital shifts. A single FORTRAN program was written to retrieve all SADE information to be analyzed.

The size of a pixel is about tenfold bigger on the SADE data than on LANDSAT-1 CCT data. This circumstance prevents the use of the available ground truth data because detail is insufficient to establish a reliable training site. The lack of adequate ground truth determined the need for a different approach for the analysis. Boundaries of each township in Boone County were located on the SADE tape for each digitized MSS band. A frequency distribution of gray tones was obtained from a randomly chosen township, Garden, from the band on which soybean crops were easily identifiable. That was on August 26 imagery, MSS 7, where soybean crops show the highest response among all features. Statistical reports showed that the percentage of soybeans planted during the 1973 growing season occupied 33.8% of the Garden Township area. Arbitrarily assuming that the statistical reports were accurate, that percentage was correlated with the frequency distribution to establish what group of gray tones provided a similar percentage of soybean-occupied area in Garden Township. In other words, the gray tones showing a cumulative percent distribution equal or less than 100 - 33.8 = 66.2 were considered as resulting from areas not occupied by soybeans. From the remaining gray tones up to 255, all pixel responses were assumed to have been originated by soybean crops. By extrapolation of the gathered information, soybean fields on the remaining Boone County townships were classified using the same imagery.

By visually examining the resulting computer printout, it was evident that errors resulted either from the approach used to classify the imagery or from the digital product rendered by the SADE system. The color photographs taken from the television screen at digitizing time seem to confirm this assumption, when compared to the digitized imagery. Area measurements performed in each township and compared to the available statistics confirmed what was visually obvious.

It was decided to correct the SADE data. After visually examining the digital data, it was reasoned that a plot of the mean value of each scanline included within the boundaries of Boone County versus the respective scanline would show points more or less scattered along an average value of all scanline means, positioned with no slope, parallel to the abscissa. Those mean values were obtained by calculating the linear regression equation and a slope ($b = 0.14$) resulted confirming our visual analysis.

The digital responses in Garden Township were corrected by adding or subtracting the difference between the estimated value calculated using the linear regression equation (y) and the average value yielded by all scanline means ($\bar{y}$). In this way, the slope was eliminated from a new plot of corrected values. Following the same procedures previously described, a frequency distribution of digital responses for Garden Township resulted in a different cut-off response which was used to classify soybean crops in the whole county after all data were corrected.

Considering August 26 images, MSS 7, corn responses showed intermediate response values. Thus, after the highest values were classified as soybean crops, the remaining gray tones were considered as indicators of corn crops present. The percentage indicated by the statistical data was used to discriminate corn responses.

Corn and soybean crop areas estimated in this manner were compared to the values given on the statistical report for the remaining townships.

Forest areas were located in Boone County following similar procedures. The area occupied by forests in Yell and Des Moines Townships was 2620.4 hectares as estimated by Carlson _et al_. (1974). A frequency distribution of gray tones for that township showed that values equal or less than 87 on January 4 imagery were presumably forested areas. The presence of forests was enhanced by a snowcover at the time of the satellite pass. Two townships were pooled in this case to avoid uncertainties regarding the Des Moines River path separating them.

Obviously, the procedures used to classify major crops in Boone County cannot possibly be used on an operational forecasting survey. They were used to acquaint ourselves with SADE data. The idea behind this scheme was to facilitate a later visual classification to roughly test the potential of SADE data applied to crop area measurements, yield forecasting, and land-use recognition.

The planned visual handling of the data proved not to be very helpful so a clustering technique was developed to objectively classify digitized ground surface features.

Cluster analysis is a simple method of searching for relationships in a large symmetrical matrix. It is a straight-forward, logical, pair-by-pair comparison between samples, objects, or variables. The purpose of any cluster analysis is to discover groupings among categories on the basis of similarity coefficients. Once the similarity coefficients between all pairs of categories have been calculated, similar categories are clustered to form groups. Results are presented in an easily understood two-dimensional hierarchical diagram on which the "natural breaks" between groups will be obvious. Groups can also be selected at any desired level of similarity or dissimilarity (Parks, 1966).

There have been described several measures of similarity. The one used here was a simple distance function. The percentage cumulative frequency distribution of gray tones on each SADE imagery for Boone County was found. A data matrix was built with the gray tones as categories and their respective cumulative percentages as the observed value for each category. In other words, there were 256 categories, each one with one observed value, the corresponding cumulative percent. Next a distance matrix (a half-matrix in fact) was obtained as follows: from each member of the data matrix, all the members located above it, if any, are subtracted one at a time, successively constituting the row on the half-matrix. The same is done by subtracting each member from itself. The resulting half-matrix has diagonal values equal to zero, indicating exact similarity due to the subtraction of each member from itself. For each row (i) on the matrix, this is represented by the following equation:

$$M_i = C_i - C_{1 \text{ to } i}$$

where M = half-matrix value
C = percentage cumulative
i = 1, 2, 3, ..., n gray tones

The mutual relationships among categories is then displayed by means of a dendrograph computer program, available at Iowa State University, written by McCammon and Wenninger (1970). Both the dendrograph program and the program used to build the distance matrix were combined into one nonsupervised computer program called ADD, acronym for Analysis of Digital Data. Slight modifications were introduced into the dendrograph program to adapt the dichotomous splitting of groups at each hierarchical level to the particular characteristics of the data being used when analyzing satellite digital information.

The ADD program was used to classify SADE imagery in order to estimate the areas occupied by corn and soybean crops and forests in Boone County. These estimates were later compared to the available information from other sources or procedures. Once areas occupied by major crops were estimated, probable corn yields were calculated using the moisture-stress approach developed by Shaw (1974) and the equation used by Thompson (1969a). Soybean yields were also estimated by using Thompson's equation (1970). Estimated yields were compared to information provided by statistical reports.

With the ADD program available, it seemed only logical to see what would happen when it was applied to LANDSAT-1 data. Thus, the imagery recorded on the earlier described working tape was classified and the results compared to ground truth data and to previous classifications.

Skylab imagery covering Mills County in southwest Iowa was next subjected to a digital analysis performed with the ADD program, for the purpose of classifying the soils. A resource area map of that county, recently modified in part by J. R. Nixon[1], was used to compare the results of the classification. A Bausch and Lomb Zoom Transfer Scope

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[1] Soil scientist, Party Leader, Soil Conservation Service, Malvern, Iowa.

available at the Department of Forestry of Iowa State University, was used to investigate the correlation among features classified by ADD and the Skylab imagery from which the digital information resulted.

RESULTS AND DISCUSSION

The 1973 crop growing season was adequately covered by LANDSAT-1 passes over Boone County at critical times with respect to crop development. The imagery used was of good quality and essentially cloud-free.

Previous analysis performed on this multispectral, temporal imagery by Carlson and Fenton (1975) seemed promising to them for crop, forest, and soil classification. They used classical interpretative techniques on photographic material. They did not attempt to estimate acreages using those techniques, feeling that that task would be most readily accomplished by automatic computer processing of magnetic digital tapes. The visual analysis of LANDSAT-1 black and white and color products which they initiated was continued here to attain means for accurate crop-type separation.

Photographic material obtained by the satellite over a portion of central Iowa on the selected dates and MSS (multi-spectral scanner) bands is presented in Figures 9 through 11. Resolution elements having high values on the CCT's (computer compatible tapes) indicate highly reflective surfaces and appear darker in the LANDSAT-1 black and white photographic material. Conversely, resolution elements presenting low values denote relatively lower reflective surfaces. The greater the difference among values obtained from different ground surface features, the greater the contrast observed on the photographic material and the better the chances for successful recognition of features. The usefulness of the imagery used here for crop and forest identification purposes seems obvious. The contrast among features is generally marked.

Figure 9. Black and white enlargement of MSS band 7, covering a portion of central Iowa on May 10, 1973; Image # E-1291-16335

Figure 10. Black and white enlargement of MSS band 5, covering a portion of central Iowa on August 26, 1973; Image # E-1399-16323

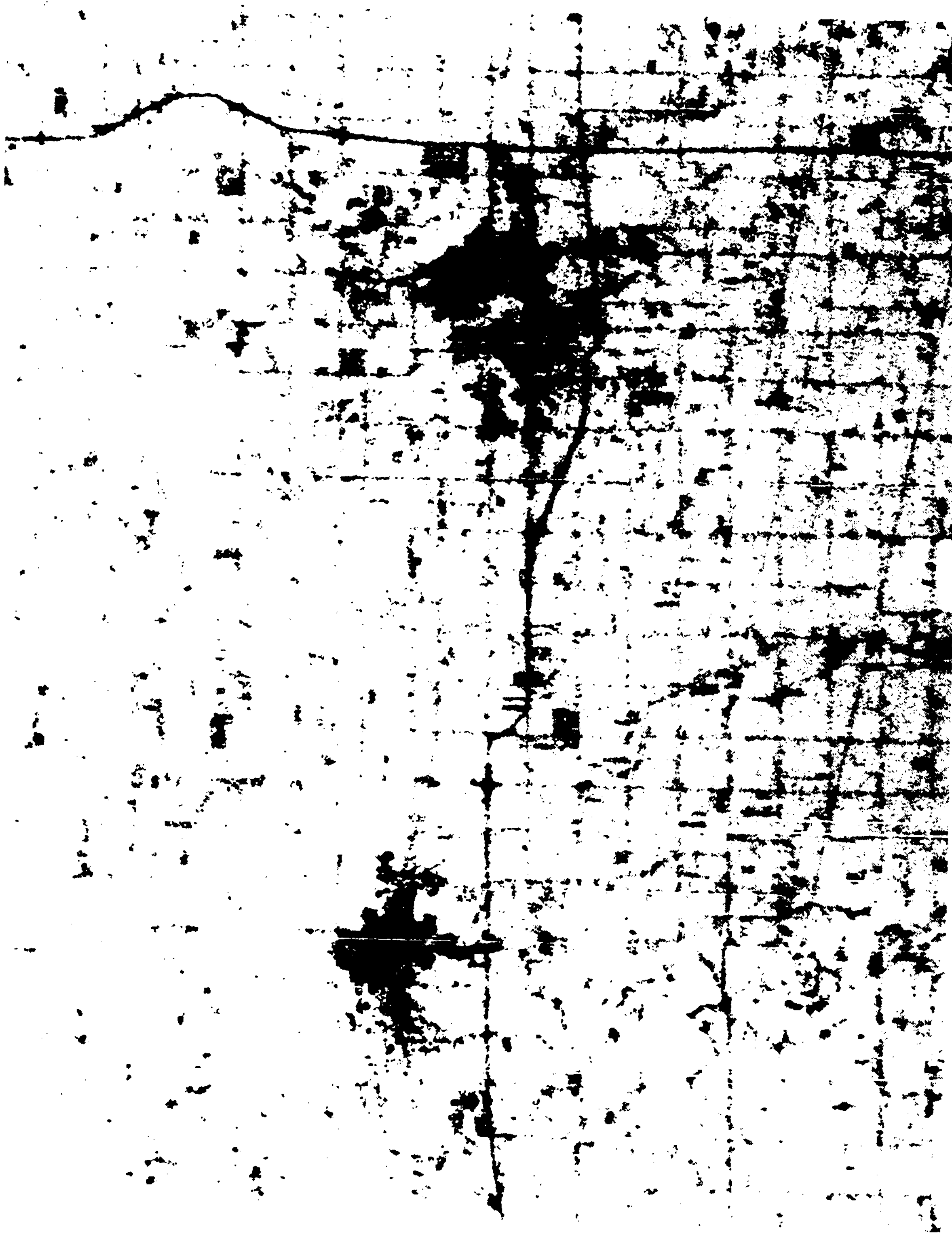
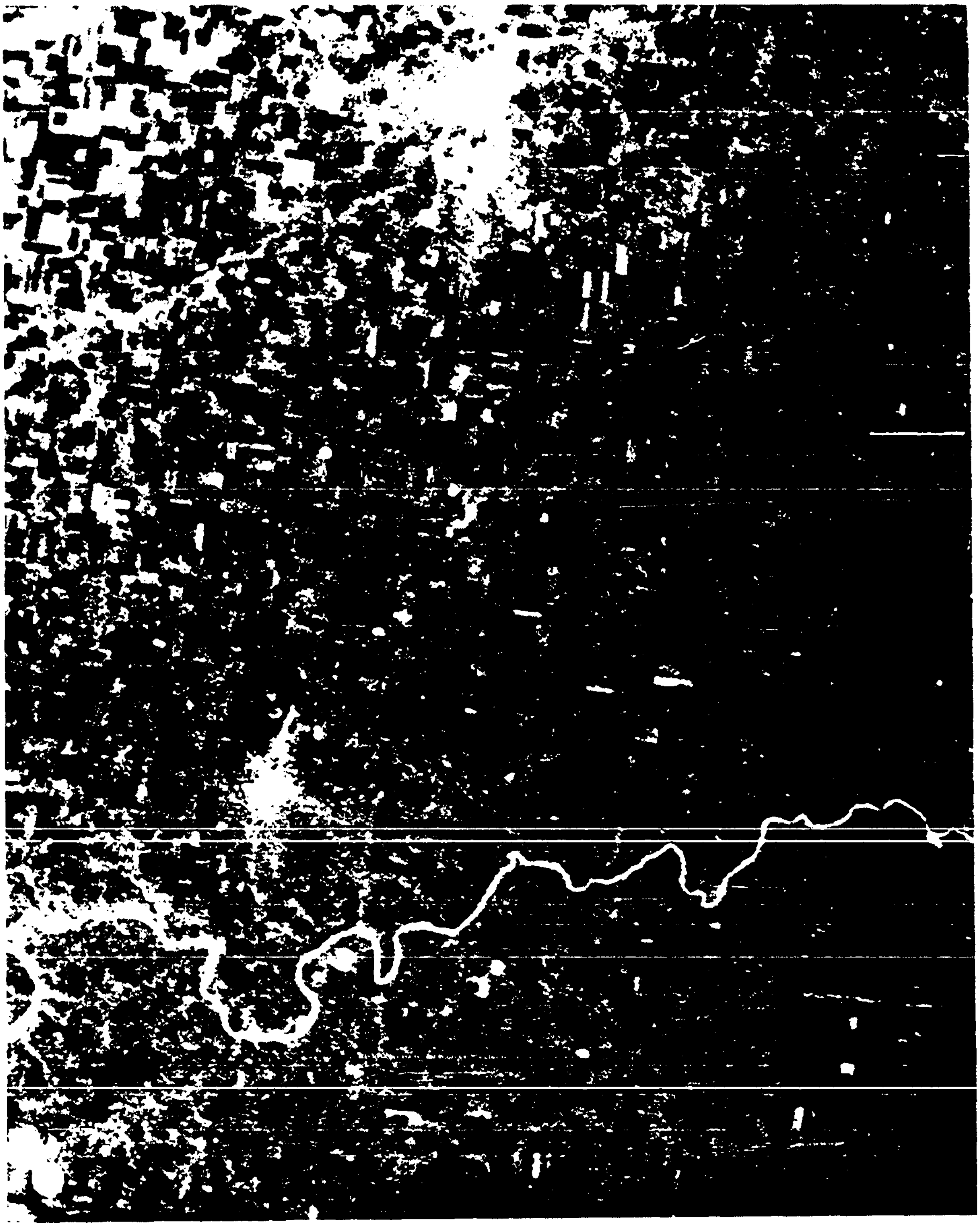


Figure 11. Black and white enlargement of MSS band 7, covering a portion of central Iowa on August 26, 1973; Image # E-1399-16323



On the springtime imagery shown in Figure 9 (May 10, MSS 7) towns, forest lands and areas occupied by crops which provide early season ground cover (alfalfa, pasture) appear dark colored, yielding contrast with respect to lighter areas which correspond to fields in various states of early season tillage (corn, soybeans, oats, etc.) and bodies of surface water. This separation occurs because actively growing vegetation strongly reflects near infrared radiation when compared to plowed and stubble-covered fields and surface water.

The only imagery used here which was obtained using the visible portion of the electromagnetic spectrum is shown in Figure 10 (August 26, MSS 5). This band provides useful information regarding the geographical location of ground features because roads and towns appear dark when compared with other land uses. Note that some oats and alfalfa fields are dark in appearance because of recent harvesting or plowing.

August 26, MSS 7 (Figure 11) provides information needed for distinguishing between corn and soybean crop responses. Soybean occupied areas (dark color) separate well from most other crop types (gray color). Surface areas covered by water and bare soil appear white on this imagery as was evident also in Figure 9 (May 10, MSS 7).

The potential of these images applied to a multispectral, temporal analysis of vegetation types seemed visually evident from the start of this work. There remained to be demonstrated their effectiveness for obtaining crop inventory estimates, and this was the main goal of this study. Results obtained using various techniques are presented next.

Area Estimates

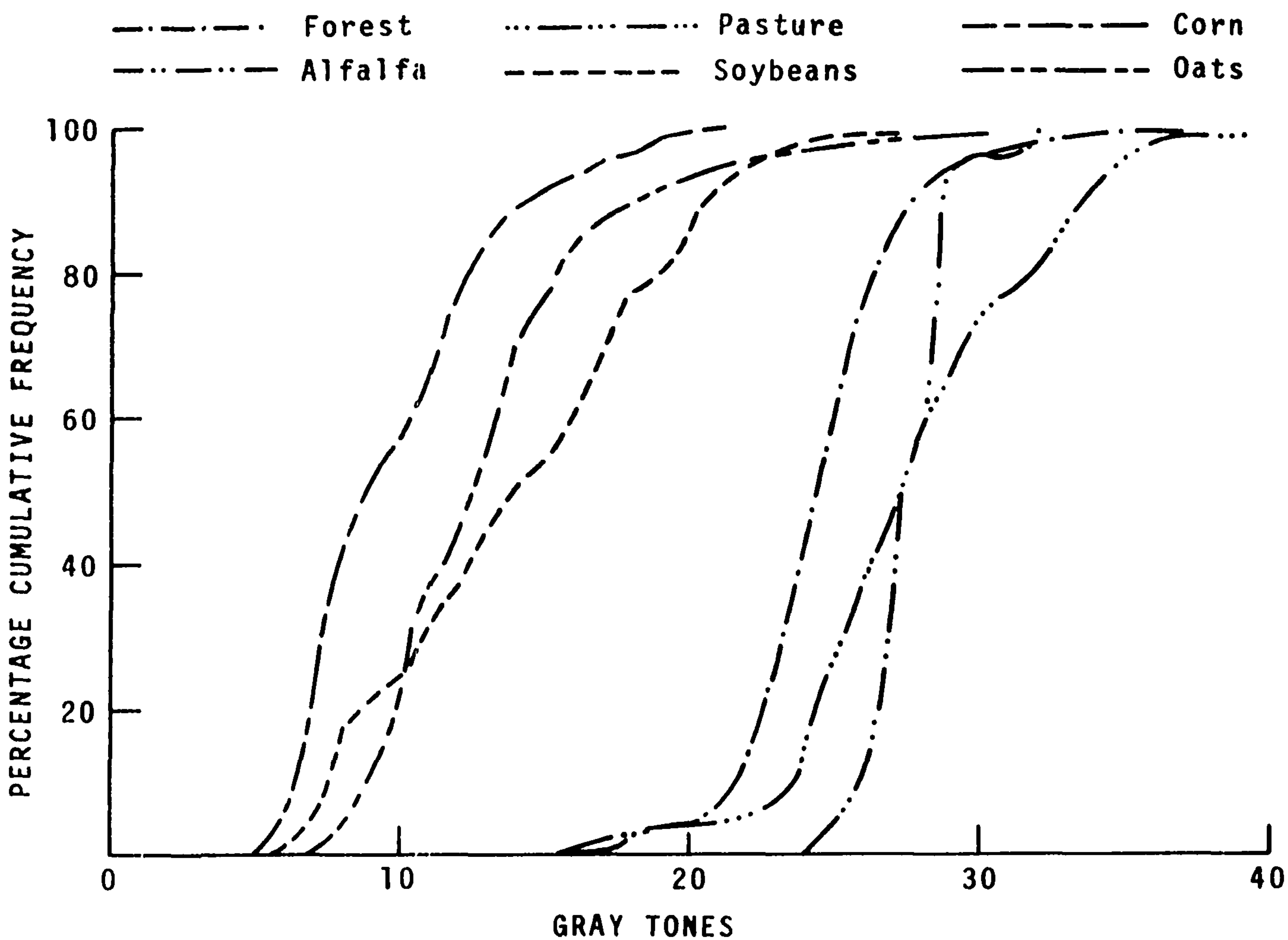
From LANDSAT-1 data

Figures 12 through 14 present results obtained when digital spectral responses for major crops and other land use categories were extracted from the working magnetic tape with the help of the available ground truth information previously discussed, and the satellite black and white photographic material.

Visually observable features present in the black and white imagery for May 10 (Figure 9) are numerically depicted by the percentage cumulative frequency distributions in Figure 12. Spectral responses for corn, soybeans, and oats are easily distinguishable from forest, alfalfa, and pasture spectral responses; 95% of the values corresponding to corn crops are included between the gray tone levels 5 and 17. The same percentages for soybeans and oats are both encompassed between the gray tones from 5 to 22. Gray tone values greater than 22 may lead to a possible 100% identification of alfalfa fields, about 95% of the pastures, and 85% of forests, provided that other imagery can be used to differentiate among these categories.

Figure 13 confirms the usefulness of August MSS 5 imagery for separating roads, though imperfectly, from other land uses. Responses from urban areas were not carefully studied so they are not included here, but Figure 10 shows that those spectral responses were very similar to those produced by roads. Other land use separations seem very improbable to perform on this imagery.

Figure 12. Percentage cumulative frequency distribution of digital responses observed on training sites on May 10 data



Forest
Pasture
Corn
Alfalfa
Soybeans
Oats
PERCENTAGE CUMULATIVE FREQUENCY
100
80
60
40
20
0
10
20
30
40
GRAY TONES

Figure 13. Percentage cumulative frequency distribution of digital responses observed on training sites on August MSS 5 data

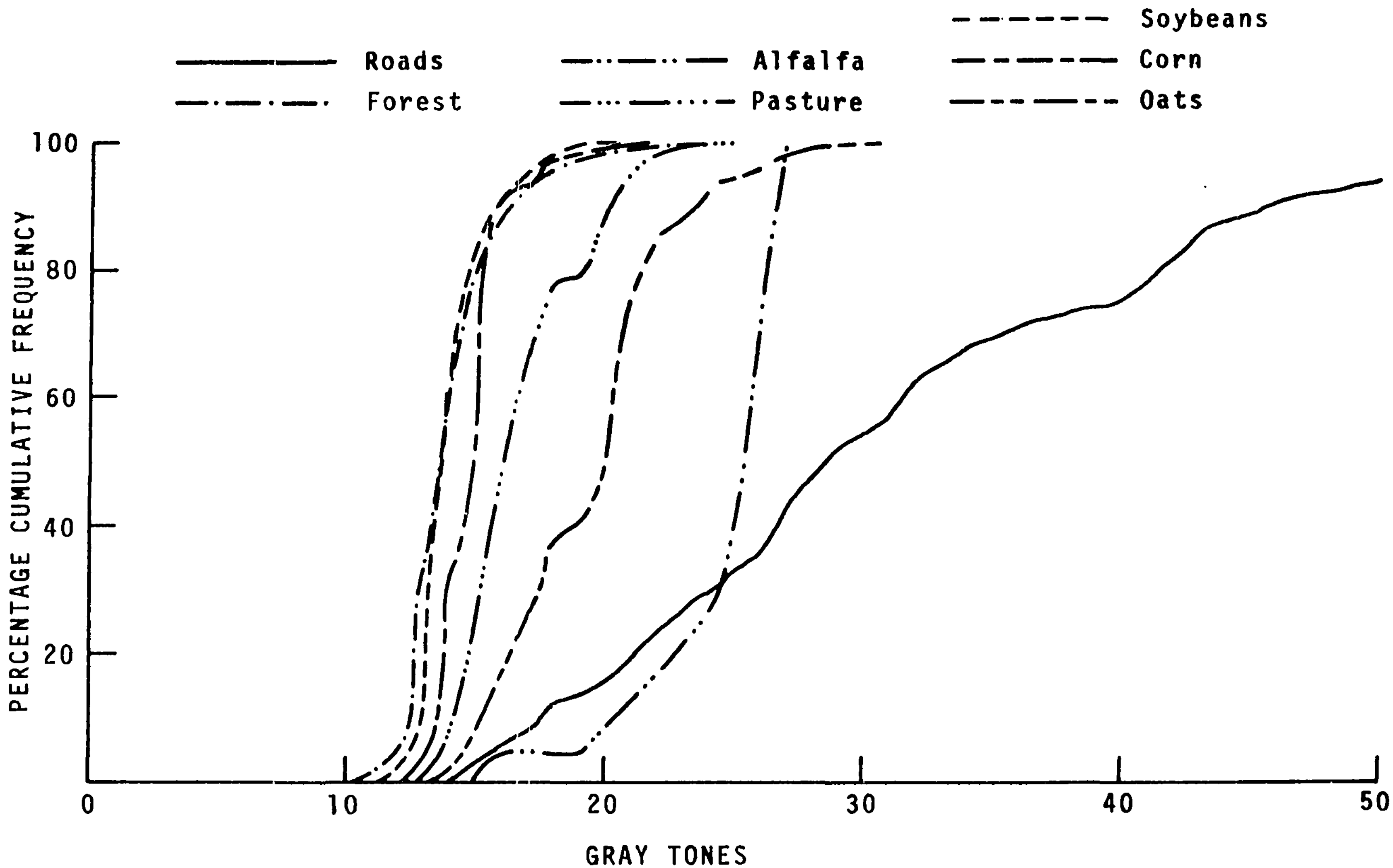
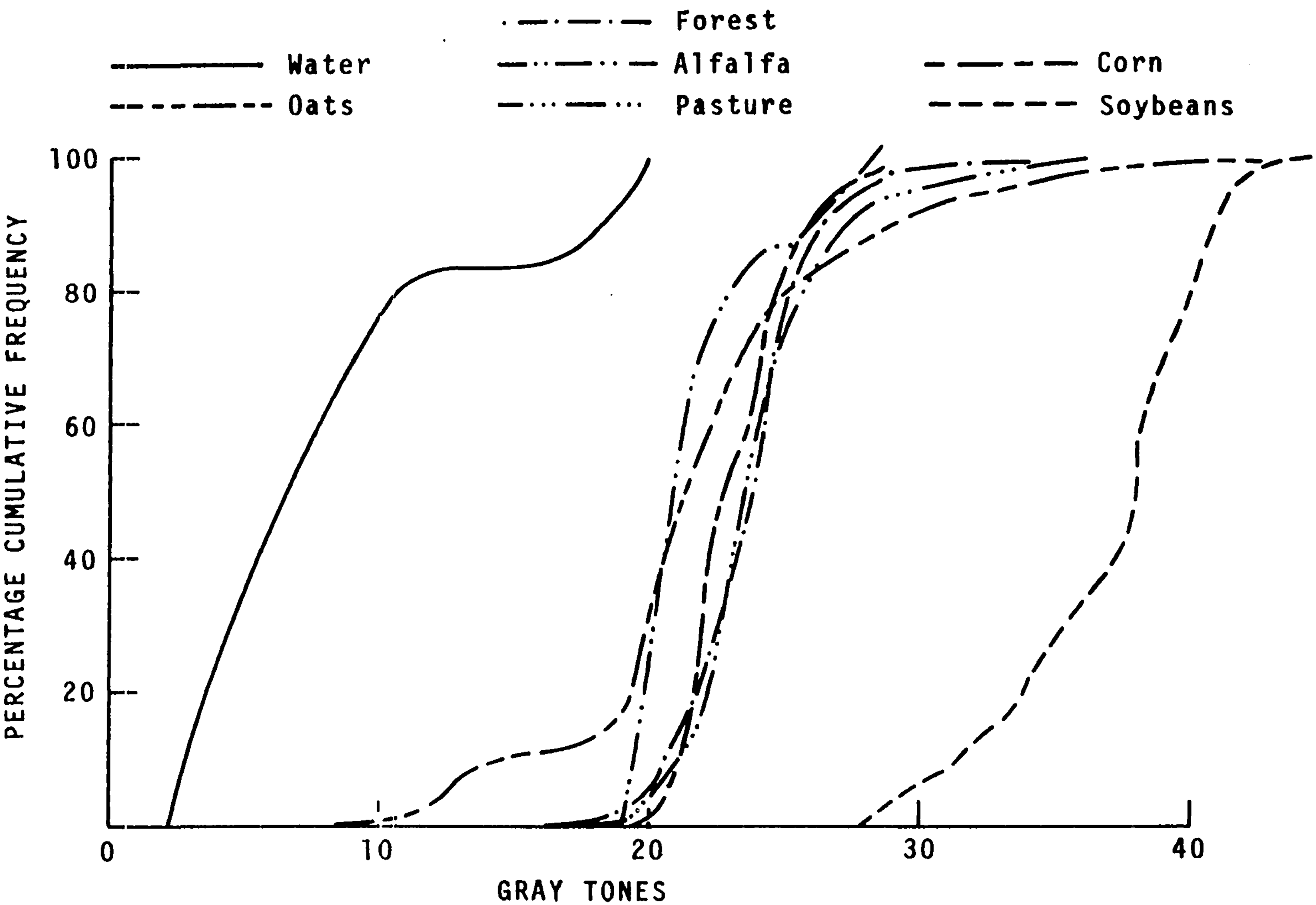

Soybeans
Roads
Alfalfa
Corn
Forest
Pasture
Oats
100
80
60
40
20
PERCENTAGE CUMULATIVE FREQUENCY
0
10
20
30
40
50
GRAY TONES

Figure 14. Percentage cumulative frequency distribution of digital responses observed on training sites on August MSS 7 data


Forest
Water
Alfalfa
Corn
Oats
Pasture
Soybeans
PERCENTAGE CUMULATIVE FREQUENCY
100
80
60
40
20
0
10
20
30
40
GRAY TONES

Soybean crops were very reflective on MSS 7 on August 26 (Figure 14) producing spectral responses greater than 27; misclassification will occur when trying to identify soybean crops using this image due to some high values also obtained from corn, forest, and pasture areas. Another category which is easily identifiable is water. It was not readily distinguishable using the May 10 image because the spectral response of bare soil was quite similar.

The laboriously obtained numerical information, aided by the visual observation of the black and white imagery, can be combined in many ways for recognition and classification purposes. The registered information stored on the working tape permitted the use of several approaches using the data represented in Figures 12 to 14. For instance, if the digital data are correct and representative of areas surrounding the training site, the computer can be instructed to classify, as roads and urban areas, all picture elements having high values on August MSS 5 imagery (Figure 10). This would not result in a total identification for those categories because, at most, about 60% of their corresponding picture elements are completely separable from other categories having gray tone values greater than 27; however, this can be refined later in the classification process. With one category established, the computer can proceed with the analysis of those resolution elements still remaining to be identified.

Continuing the analysis of August MSS 5 imagery, some partial identifications of pasture, oats, and alfalfa fields are possible because gray tones between 16 and 26 show pasture fields to have low values, while alfalfa fields present high values and oat fields intermediate ones. Some corn and soybean fields and forest lands would be misclassified, but if all picture elements having values between 16 and 26 on August MSS 5 are investigated using the other images, misclassification risks are greatly diminished. Forests would not be greatly misclassified, for they present relatively low values on August MSS 5, and thus their picture elements are not considered when analyzing May 10 data. The remaining possible identifiable categories have low values on August MSS 5 imagery. Soybean and corn crops have low values on May 10, but forests present high values, thus providing a basis for separation of these categories. Finally, resorting to August MSS 7 data (Figure 14) after all previous categories have been classified, soybean and corn crops are easily differentiated. A last category may be established by considering low spectral responses indicating bodies of surface water in this MSS band.

Another similar approach was developed and is illustrated on Table 4. The computer was instructed to classify as soybean crops all picture elements presenting relatively high spectral responses on August MSS 7 data. The remaining categories were further investigated, based on the spectral responses indicated on August MSS 5. Those picture elements having high spectral responses were classified as urban areas or roads with the others being separated into two groups showing low and intermediate spectral responses. Each one of these groups finally resulted in the remaining categories being established by analysis of May 10 MSS data. The results obtained in the 12-Section area in Colfax Township using this approach are presented in Table 5. The total number of resolution elements actually belonging to each category in this table

Table 4. Classification scheme applied to working tape data encompassing a 12-section area on Colfax Township

- Aug MSS 7
  - $\geq$33: Soybeans
  - <33: $\rightarrow$Aug MSS 5
    - $\geq$28: Towns & roads
    - 20-27: $\rightarrow$May
      - $\leq$17: Oats
      - 18-25: Alfalfa
      - 26-31: $\rightarrow$[(May+Aug MSS5-Aug MSS7)-25]
        - $\leq$0: Alfalfa
        - 1-5: Towns & roads
        - $\geq$6: Alfalfa
      - $\geq$32: Alfalfa
    - <20: $\rightarrow$May
      - $\leq$5: Water
      - 6-22: $\rightarrow$Aug MSS 7
        - $\leq$10: Water
        - 11-19: Forest
        - 20-29: Corn
        - $\geq$30: Soybeans
      - 23-29: $\rightarrow$Aug MSS 7
        - <26: Forest
        - $\geq$26: Pasture
      - $\geq$30: Pasture

Table 5. Land-use classification performed on the 12-section area of Colfax Township

Land-use category	Number of resolution elements	% correct	Number of resolution elements classified into: F	P	R	A	O	C	S	W
Forest (F)	117	3.4	4	8	4	24	16	35	26	0
Pasture (P)	239	12.1	9	29	7	51	27	52	64	0
Towns & roads (R)	168	54.8	1	2	92	32	19	12	10	0
Alfalfa (A)	200	13.5	4	45	9	27	5	43	67	0
Oats (O)	327	49.5	16	1	8	24	162	80	34	2
Corn (C)	2672	78.2	38	41	13	50	54	2090	381	5
Soybeans (S)	2625	80.4	14	41	17	50	71	322	2110	0
Water (W)	12	41.7	0	0	2	1	4	0	0	5
Totals	6360		86	167	152	259	358	2634	2692	12
%			73.5	69.9	90.5	129.5	109.5	98.6	102.6	100.0

Total diagonal values: 4 + 29 + 92 + 27 + 162 + 2090 + 2110 + 5 = 4519

Overall performance: (4519/6360) * 100 = 71.0% correct was determined by aligning the ground truth with the satellite computer output. This permitted evaluation of misclassifications. No attempt was made to classify resolution elements for which there was no way to accurately correlate them to the ground truth available. This occurred within the area occupied by the Iowa State University Agronomy Farm in Sections 8 and 9 because many small experimental plots yielding responses integrated from very dissimilar ground features were present. The 80% accuracy obtained in the identification of corn and soybean crops may appear as acceptable, but somewhat low. The percentage of resolution elements classified as corn which actually were not corn [(544 x 100)/2672 = 20.4%] was compensated by those resolution elements erroneously considered in other categories, when they actually corresponded to corn [(582 x 100)/2672 = 21.8%]. Because of this circumstance, 2634 resolution elements were assigned to the corn category out of 2672 actually known as belonging to it. This resulted in a 98.6% overall classification for corn.

Similar results were obtained for soybean crops; 22.1% of the resolution elements classified as soybean were not soybean while 19.7% of those actually corresponding to soybean were assigned to other categories. A total of 2692 resolution elements were assigned to the soybean crops category with 2625 resolution elements actually known as soybean. This resulted in a slight overestimate (2.5%). Obviously, nothing guarantees that this compensation between both types of errors will always occur. However, results obtained classifying in the same way, the entire Colfax Township (Table 6), seem to give support to the supposed compensation. Corn and soybean crops were slightly overestimated

Table 6. Satellite derived land-use classification in Colfax Township, Boone County, compared to Crop Reporting Service (CRS) information

Category	From LANDSAT-1 hectares	From LANDSAT-1 %	From CRS hectares	From CRS %	$\frac{\text{(LANDSAT-1) - CRS}}{\text{LANDSAT-1}}$ 100
Corn	3569.8	41.6	3441.2	40.2	3.6
Soybeans	3666.6	42.8	3379.2	39.2	7.8
Oats	399.3	4.7	148.4	1.7	62.8
Pasture	250.2	2.9	288.4	3.4	-15.3
Alfalfa & other crops	339.3	4.0	218.4	2.5	35.6
All other land					
Forest	182.5	2.1			
Towns & roads	140.5	1.6	1093.2	12.8	-218.2
Water	20.6	0.2			
	8568.8	99.9	8568.8	100.0	

(3.6% and 7.8%, respectively).

It appears that this classification procedure included too many categories and that this introduced sources of misclassification for major crops. This leads to uncertainty in the selection of cut-off spectral responses chosen from the digital data. The low accuracies obtained for categories other than soybeans and corn can be attributed to the small number of fields which were available within the training site to study their responses and to characteristics of the imagery which will be discussed later. Furthermore, those fields which were analyzed generally had very small areas and/or irregular shapes. Forest lands were not very accurately identified in Colfax Township. This is attributable to the scarce presence of this category within the township;

in fact less than 2% of the known ground truth corresponded to forests in the 12-section area, and the remaining sections of the township do not show a different situation.

Ground truth data were available for Sections 10 and 15 in Worth Township, and both of these sections contained mostly pasture and forested lands. Therefore, a classification performed in these sections yielded the results given in Table 7 for those two categories. Some minor over-estimations are still observed, but results are considered close enough, considering the uncertainties arising from the relatively small area classified and from section registration difficulties in the computer printout. No attempt was made to compare these results with realigned ground truth data, but it was visually obvious that many of the misclassifications observed were due to some forest sites being classified as corn fields. The inverse situation was observed in Colfax Township, where about 30% of the resolution elements classified as forests corresponded in fact to corn crops (Table 4).

Digital field acreage estimates obtained on a 14-section area (Sections 7 to 18, Colfax Township, and Sections 10 and 15, Worth Township) were correlated to acreages estimated from low-level images. The results are shown in Figures 15 and 16. Good agreement between estimates is observed, leaving no doubt that, if a near perfect classifier is ever developed, it will very accurately estimate areas.

The evaluation of the classification procedures performed by realigning the available ground truth has to be taken only as giving some general means for assessing accuracy of the procedures used. It is highly doubtful that an exact agreement could be obtained between

Table 7. Pasture and forest land areas estimated on satellite imagery for Sections 10 and 15, Worth Township, compared to ground truth areas

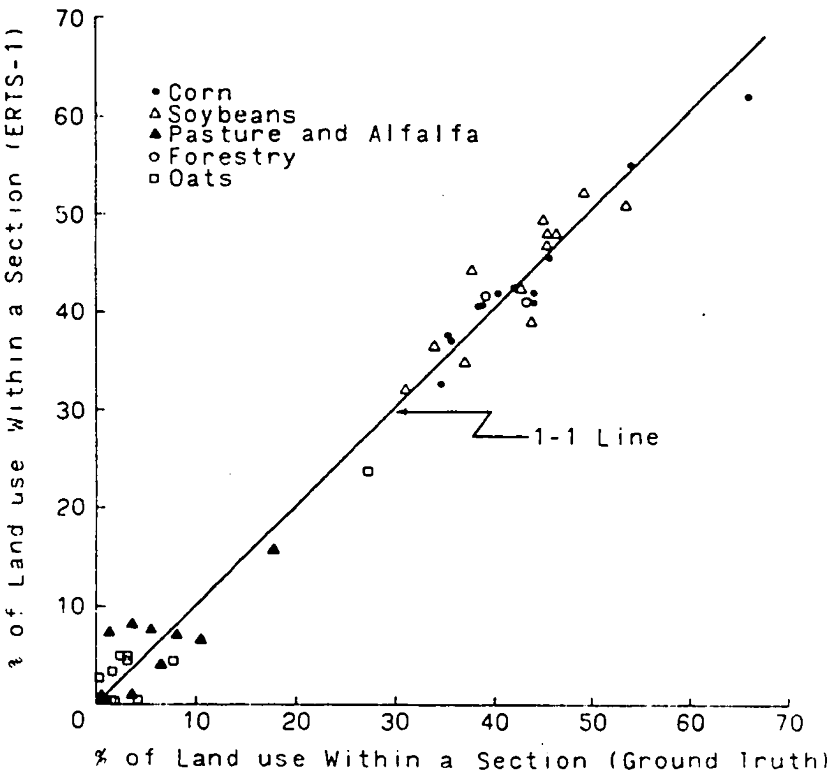
Category	LANDSAT-1 estimated area hectares	Ground truth area (GT) hectares	(LANDSAT-1) - GT / LANDSAT-1 %
Forest			
Section 10	102.1	101.5	
Section 15	101.2	112.5	
	203.3	214.0	-5.3
Pasture			
Section 10	58.5	84.4	
Section 15	41.8	38.5	
	100.3	122.9	-22.5

the path followed by the satellite and that assumed when realigning the ground truth. Thus, registration of digital data with realigned ground truth must be regarded as being only approximate. If the Zoom Transfer Scope had been available during the earlier stages in this study, the situation would have been different. However, field acreage estimates obtained on the realigned training area showed good agreement for all land use categories when compared to those acreages estimated from the unrealigned ground truth. An overall $R^2 = 0.98$ was obtained.

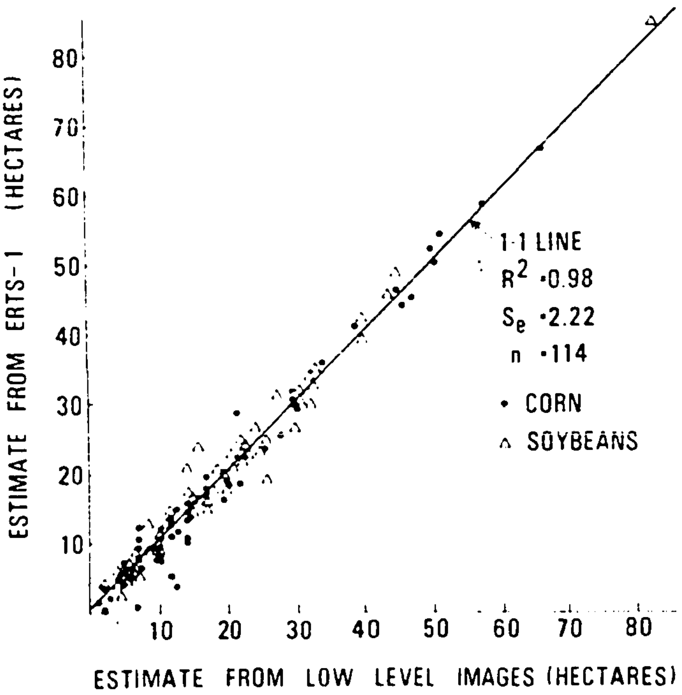
Positive transparencies corresponding to the data sets used here had been previously registered by Carlson et al. (1974) using a miniadcol system (I^2S). However, the registration of digital data sets is tedious and time consuming. Besides, perfect registration would probably never result because of orbital and instrument constraints and variabilities.

Figure 15. A depiction of field acreage LANDSAT-1 estimates (%) versus ground truth (%) for five crop or land types within 14 sections in central Iowa

Figure 16. Individual corn and soybean field acreage estimates from LANDSAT-1 versus ground truth



70
60
50
40
30
20
10
0
10
20
30
40
50
60
70
• Corn
△ Soybeans
▲ Pasture and Alfalfa
○ Forestry
□ Oats
1-1 Line
% of Land use Within a Section (ERTS-1)
% of Land use Within a Section (Ground Truth)



80
70
60
50
40
30
20
10
10
20
30
40
50
60
70
80
1-1 LINE
R² = 0.98
Sₑ = 2.22
n = 114
• CORN
△ SOYBEANS
ESTIMATE FROM ERTS-1 (HECTARES)
ESTIMATE FROM LOW LEVEL IMAGES (HECTARES)

Thus, any classification approach not requiring registration can lead to elimination of that source of uncertainty. This approach was developed and tested in Section 10, Colfax Township, where most crops representative of central Iowa, except forested lands, are present. In each data set, resolution elements which can easily be recognized and computer-extracted are assigned to the corresponding class and are counted. This was done using May 10 data, assigning all values higher than 22 (see Figure 12) to a category where forest, alfalfa, and pasture are initially pooled. The same is done using August MSS 5 data including all values exceeding 19 within a category representing towns and roads, some oats, alfalfa, and bare soils. Finally, all values higher than 28 on August MSS 7 data are assigned to the soybean crops category. The total number of resolution elements remaining not having been classified into one of the previous categories are assigned to the corn crop category. The results obtained were compared to the realigned ground truth, and they are presented in Table 8.

Except for corn crops, all categories improved greatly in percent correct identification by comparison with the classification requiring registration (Table 5). Another run using this described classification procedure was attempted. This time, by considering as soybean crops values equal or higher than 33 on May data, the percentage correct classification for corn crops increased to 76.3, but decreased to 77.0 for soybeans. Because both corn and soybean crops occupy most of the agricultural lands in central Iowa, any modification introduced in the classification procedure used in the detection of any one of them alters the results to be obtained for the other major crop, due to their similar

Table 8. Land use classification using nonregistered satellite data; Section 10, Colfax Township, Boone County

Land use category	Number of resolution elements	% correct	Number of resolution elements classified into:			
			P	T	C	S
Pasture, alfalfa, forest (P)	65	66.1	43			
Towns, roads, etc. (T)	65	52.3		34		
Corn (C)	194	61.8			120	
Soybeans (S)	256	88.7				227
Misclassifications			35	46	74	75
Totals	580		78	80	194	302

responses over certain ranges in gray tones. Thus, the correct distinction between corn and soybean crops is a crucial one.

The classification performed with no registration was not further investigated on larger areas included in the working tape; so, no conclusive evidence is available regarding its applicability to digital satellite data at this time. The simplicity of this approach is appealing, and this subject will be considered later in this chapter in relation to the classification of the working tape data obtained with the nonsupervised computer program developed in the final stages of this research.

<u>From SADE data</u>

<u>Agricultural lands area measurements</u> The classification procedure requiring no registration was further studied using SADE data.

Results obtained from August MSS 7 data for soybean and corn crops are presented in Tables 9 and 10.

Table 9. Area estimates for soybean crops in Boone County obtained from corrected August MSS 7 SADE data compared to Crop Reporting Service (CRS) information

Township	SADE estimated area; hectares	CRS area hectares	$\frac{\text{SADE-CRS}}{\text{SADE}}$ %
Grant	3041.0	3013.2	0.9
Pilot Mound	1754.1	1524.8	13.1
Dodge	2693.2	2932.4	-8.9
Harrison	1873.3	2902.0	-54.9
Amaqua	4422.4	3845.2	13.0
Yell	1704.4	1286.8	24.5
Des Moines	2191.3	2347.6	-7.1
Jackson	2728.0	3765.2	-38.0
Beaver	4034.8	3329.6	17.5
Marcy	2837.3	3163.2	-11.5
Worth	1441.0	1592.0	-10.5
Colfax	3036.1	3379.2	-11.3
Union	3821.2	3331.2	12.8
Peoples	2588.9	3288.8	-27.0
Cass	511.8	976.0	-90.7
Douglas	710.6	654.0	8.0
Garden	2335.4	3355.2	-43.7
Totals	41724.8	44686.4	-7.1

Table 10. Area estimates for corn crops in Boone County obtained from corrected August MSS 7 SADE data compared to Crop Reporting Service (CRS) information

Township	SADE estimated area; hectares	CRS area hectares	$\frac{\text{SADE-CRS}}{\text{SADE}}$ %
Grant	4541.7	3914.0	13.8
Pilot Mound	2469.6	1681.6	31.9
Dodge	3647.2	3553.2	2.6
Harrison	4094.4	3688.0	9.9
Amaqua	3274.6	4074.8	-24.4
Yell	2449.7	2215.6	9.6
Des Moines	3120.5	2595.2	16.8
Jackson	4720.6	4081.6	13.5
Beaver	3771.5	3861.6	-2.4
Marcy	4685.8	4183.2	10.7
Worth	2613.7	1684.8	35.5
Colfax	5098.2	3441.2	32.5
Union	4685.8	3960.8	15.5
Peoples	5222.4	4830.4	7.5
Cass	1605.0	1078.8	32.8
Douglas	2236.0	844.8	62.2
Garden	6052.2	4470.8	26.1
Totals	64288.9	54160.4	15.8

The overall 7.1% underestimation shown for soybean crops in Table 9 is small, and the total number of hectares estimated from the corrected SADE data is in very close agreement with the total number determined by the Crop Reporting Service for that crop. However, some serious underestimates were obtained for Harrison, Jackson, Cass, and Garden Townships. Previous to the correction being decided upon, it was apparent that underestimates were localized on the northeast part of the county, while overestimates were likely to be obtained in the southwest part. Table 9 shows that by applying the correction to the digital data with the intent to compensate for the low values observed in some townships, underestimates resulted in townships where values higher than expected were apparently present before.

Overall corn crop area estimates exceeded by 15.8% those areas determined by the Crop Reporting Service (Table 10). This is not a very high overestimate as accuracies of about 80% are commonly considered acceptable when using single date imagery, as is the case here. The high overestimate observed for Douglas Township does not seem at all important, given the small percentage of corn planted there.

The location of each township on the computer printout can be regarded as a source of error in this analysis. The Des Moines River path and the identification of some towns found in the area helped to approximately locate the boundaries of each township but registration errors cannot be ruled out.

The procedures used here to estimate areas for soybean and corn crops from SADE data should be regarded only as exploratory tools. They constitute serious sources of uncertainty on the results. What looks like a problem on the digitized imagery or on the digitizing procedure for Boone County (the northeast-southwest shift from underestimates to overestimates on crop area measurements) may be due to data processing. To explore this possibility, an objective procedure was needed. The nonsupervised computer program, ADD, provided the necessary procedure. The results obtained are given on Table 11. They confirmed what was

Table 11. Area estimates for soybean crops in Boone County obtained from uncorrected August MSS 7 SADE data compared to Crop Reporting Service (CRS) information

Township	SADE estimated area; hectares	CRS area hectares	$\frac{\text{SADE-CRS}}{\text{SADE}}$ %
Grant	2096.9	3013.2	-43.7
Pilot Mound	1023.6	1524.8	-49.0
Dodge	1475.8	2932.4	-98.7
Harrison	1003.7	2902.0	-189.1
Amaqua	4000.0	3845.2	3.9
Yell	1436.0	1286.8	10.4
Des Moines	1957.8	2347.6	-19.9
Jackson	2300.6	3765.2	-63.7
Beaver	5018.7	3329.6	33.6
Marcy	3701.9	3163.2	14.6
Worth	1769.0	1592.0	10.0
Colfax	3493.2	3379.2	3.3
Union	4397.6	3331.2	24.2
Peoples	3552.8	3288.8	7.4
Cass	800.0	976.0	-22.0
Douglas	1003.7	654.0	34.8
Garden	3160.3	3355.2	-6.2
Totals	42191.6	44686.4	-5.9

already apparent, i.e., that there are two areas in the digitized information, one with values lower than expected in the northeast part of Boone County and the other with higher than expected values. As the table shows, underestimates in the northern townships range from about 20 to 189%, while overestimates in the south approach 35%. Again, the overall area estimate is still closer to the Crop Reporting Service information (-5.9% versus -7.1%).

Corn crop area estimates (Table 12) were obtained after all other land-use categories were located and their areas estimated on August MSS 5 and May unmodified digital SADE data. Again, corn-crop areas in Boone County were overestimated by about 15%. Only one serious underestimate is observed, corresponding to Beaver Township, -38.5%. Large overestimates were more frequently obtained, ranging from 20% to 56.5%. Oat fields having spectral characteristics similar to those of corn crops at the time the imagery was collected might have contributed to the observed disagreements.

Sources of errors   The larger errors observed for corn- and soybean-crop area estimates commonly occurred in townships where pasture and alfalfa fields occupy a relatively large area of the township. Those pasture and alfalfa fields of small dimensions and irregular shapes might have been either overestimated or missed because of the resolution element size in the SADE data. Individual crop fields in Iowa are frequently small and/or irregular, and some larger fields are long and narrow for convenient production practices. The multispectral scanner usually does not adequately resolve all small or irregular fields as it integrates the total radiation being reflected or emitted by disimilar ground features, when they happen to be jointly occupying a given area sensed by the scanner. This problem is accentuated when that imagery is digitized producing resolution elements which integrate responses over larger areas on the ground than that measured by the satellite.

Even radiation measured by the satellite when passing over seemingly homogeneous areas, a large field, for example, does not show uniform

Table 12. Area estimates for corn crops in Boone County obtained from uncorrected SADE data compared to Crop Reporting Service (CRS) information

Township	SADE estimated area; hectares	CRS area hectares	$\frac{\text{SADE-CRS}}{\text{SADE}}$ %
Grant	5485.8	3914.0	28.6
Pilot Mound	3200.0	1681.6	47.4
Dodge	4864.6	3552.2	27.0
Harrison	4964.0	3688.0	25.7
Amaqua	3696.9	4074.8	-10.2
Yell	2718.0	2215.6	18.5
Des Moines	3354.1	2595.2	22.6
Jackson	5147.9	4081.6	20.7
Beaver	2787.6	3861.6	-38.5
Marcy	3821.2	4183.2	-9.5
Worth	2285.7	1684.8	26.3
Colfax	4641.0	3441.2	25.8
Union	4109.4	3960.8	3.6
Peoples	4258.0	4830.4	-13.4
Cass	1316.8	1078.8	18.1
Douglas	1942.9	844.8	56.5
Garden	5227.4	4470.8	14.5
Totals	63821.7	54160.4	15.1

values all over the site. Responses usually vary then within a field and, also, between fields and especially near field boundaries.

When trying to assess the usefulness of the procedures used for recognition and classification purposes and final area estimates, it is necessary to consider that the imagery to which they are applied sometimes presents characteristics which clearly preclude attainment of a

100% correct identification. For instance, when recognition was based on bare soil discrimination from actively growing vegetation, soybeans were misclassified as pasture or alfalfa on occasion because the wet spring delayed plowing activities. These fields were later planted to soybeans and were not plowed by May 10. If late May imagery had been available, all areas to be corn or soybeans would have been plowed and successful classification would have resulted. This illustrates the importance of properly timed temporal analysis. Partly attributable to later-than-normal planting because of an excessively wet early season in 1973, most oat fields had not developed a good canopy by May 10. This response difference may not always be true during other growing seasons.

Another point arising from the imagery used in this research is that oat and alfalfa fields have a very distinct response in band 7 shortly after their harvest. This analysis was, however, restricted to late August coverage and, in some fields, regrowth produced responses similar to corn. This was a critical separation, because oat and corn fields yielded very similar responses on the May 10 image.

The spectral responses of a few corn fields corresponded closely with forested land on the May and August images. This problem was remedied by use of the January digital data stored on the SADE magnetic tape. On this image, enhanced by snow cover, forested areas were easily identified and estimated. The incorporation of the winter response minimized also the problem due to existing gradations from solid forest cover to pasture land sparsely populated with trees.

Spectral responses in populated areas sometimes yielded responses similar to some minor field types. This problem has not been completely resolved because the emphasis in this study has been directed to agricultural and forested lands.

Having considered the inherent sources of misclassification found in the images used, attention has to be given to the anomalies apparent on the August MSS 7 digitized data. No evidence was found to support the impression that something went wrong when the image was digitized. What appears to be a change in the light emitted by the respective source on the digitizing equipment may not be so. Possibly something happened when measurements were made aboard the satellite while passing over the northeast part of Boone County. The fact is that the August MSS 5 digital data also show apparently abnormally low values in the northeast corner of the county. Further, the ADD program was unable to recognize roads at all in this imagery. Only highways were detected in addition to towns. It is not known if the cited anomaly was the reason or if it was that the size of the resolution element was too large to recognize those narrow features.

This last development led the research toward investigating the possibility of the ADD computer program being at fault in dealing with the available information. The ADD program analyzed the data stored on the working LANDSAT-1 tape. The results were striking due to the marked resemblance of the computer outputs produced by the program to the satellite imagery (Figures 17 to 19). This comparison was completed using the Zoom Transfer Scope to realign the ground truth. The only misclassifications observed were those already mentioned when analyzing the quality of the original satellite imagery; that is, soybean fields being classified as pasture or alfalfa fields due to delayed plowing

Figure 17. Computer map produced by the ADD program from data collected over central Iowa by LANDSAT-1 on May 10, 1973

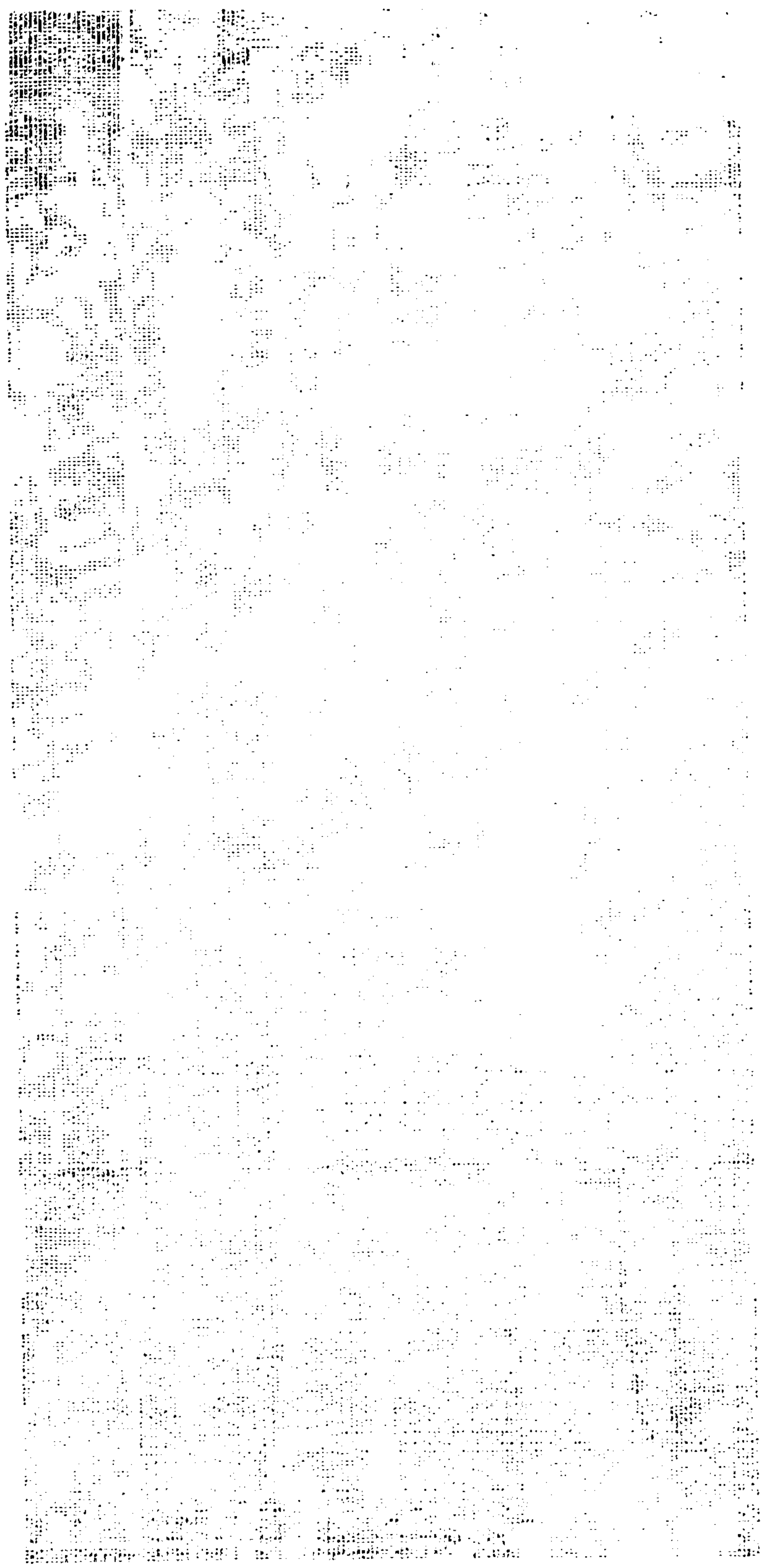
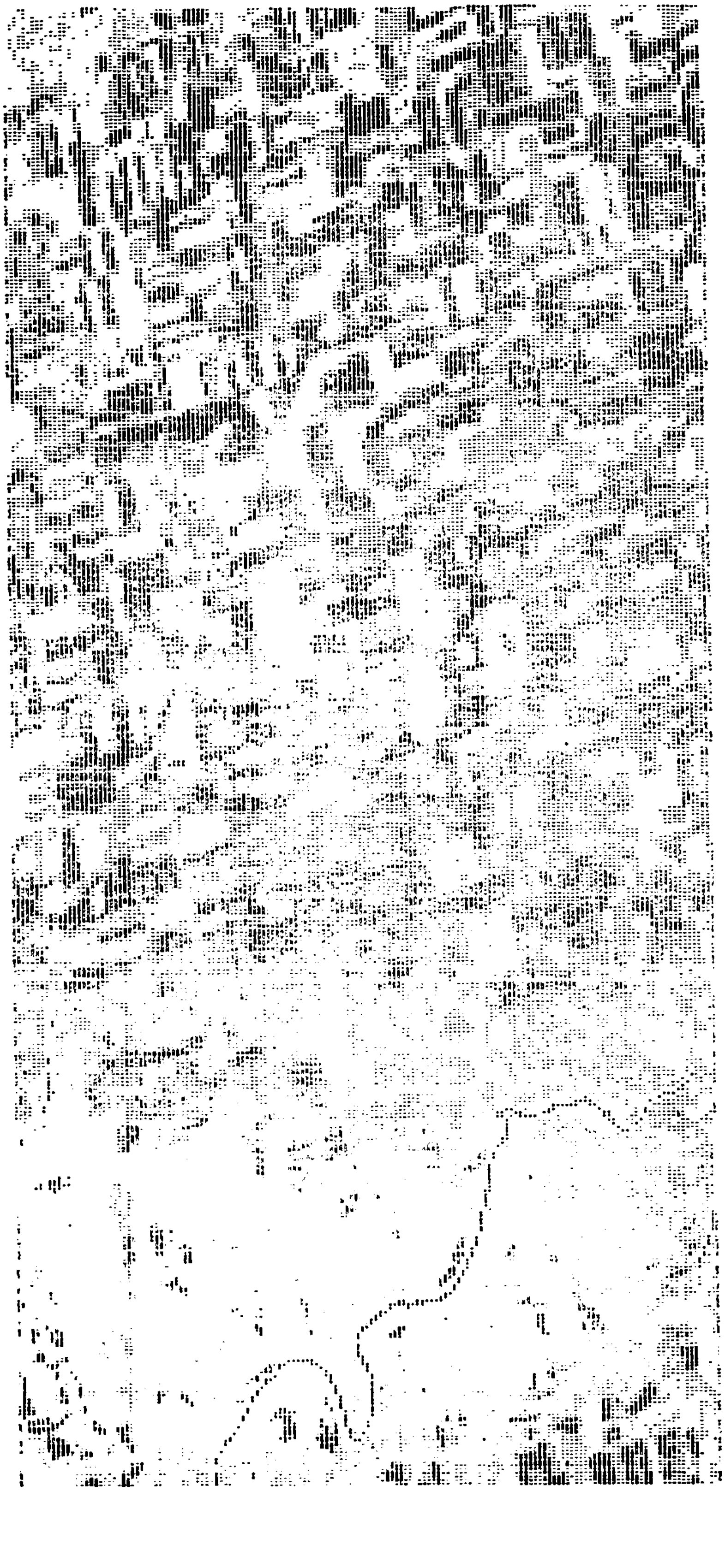


Figure 18. Computer map produced by the ADD program from data collected over central Iowa by LANDSAT-1 on August 26, 1973 (MSS 5)

Figure 19. Computer map produced by the ADD program from data collected over central Iowa by LANDSAT-1 on August 26, 1973 (MSS 7)



activities, oat fields which had not developed a good canopy by May 10, and so on. Results obtained from the August MSS 7 data with the ADD program on the 12-section area in Colfax Township showed a 90.9% correct identification of soybean crops, which is substantially higher than the usual 70% cited by Thaman (1974) for recognition of crops made on single date imagery; 987 hectares of soybean crops were correctly identified in that part of Colfax township over a total of 1146.7 hectares actually known from the ground truth to be soybean fields. It has to be pointed out that the ADD program classified the whole working tape and not just the 12-section area. Equally high degrees of accuracy were obtained for oats and alfalfa (90.8 and 92.2%, respectively). Pasture fields were overestimated by 29.5%, circumstance seemingly attributable to the imagery used. Corn-crop areas were not estimated since the purpose was to demonstrate what to expect from the ADD program capabilities. In addition, no January imagery is contained on the working tape to eliminate forest misclassifications from corn area estimates and vise versa. The most spectacular results were obtained displaying roads and towns on the map produced by ADD after analyzing August MSS 5 data stored on the working tape (Figure 18).

No theoretical justification of the ADD program is attempted here. As Dixon and Nicholson (1974) put it, the data analyst "...is quite satisfied if any advance is made in the problem area independent of the sophistication of the analysis..."

A last reflection must be stated about the information provided by the Crop Reporting Service. Throughout all analyses presented here regarding township area estimates, comparisons were made assuming that the Crop Reporting Service values were the correct ones. Perhaps that is not truly the case. The statistical information would have to be regarded only as an approximate expression of what crops actually were present.

Forested land area measurements The striking characteristic of the data stored on the SADE magnetic tape, with regard to land use classification, consisted of the contrast of the January 4 digitized imagery. This imagery (see Figure 20) clearly separates forested lands along rivers (white areas) from agricultural lands (dark areas), while gray areas correspond to towns. Note that some white areas corresponded to corn crops not yet harvested at the time the satellite passed over the region because of the excessively wet fall harvest season. This imagery is an excellent example of snow enhancement of ground features. The radiation measured from snow covered agricultural lands was much higher than that measured over forested areas. This yielded enough contrast for meaningful recognition purposes.

The ADD program applied to January 4 digital data permitted detection and estimation of the extent of forested areas in Boone County. The results are presented in Table 13. They are compared to estimates made by G. W. Thomson in all Boone County townships using five different photographic materials (Carlson et al., 1974). Those materials used were photographs taken in 1965 by the ASCS at 1:20,000 and enlarged to 1:7,920; a photo-mosaic made of the same photographs which was reproduced at 1:63,360; a photographic enlargement from LANDSAT-1 MSS 5 imagery taken on September 18, 1972 subjected to two types of analyses; and a 70 mm diapositive from LANDSAT-1 MSS 5 imagery obtained on

Table 13. Forest areas estimated from January MSS 7 SADE data versus estimations obtained from ASCS photographs and an average of several other methods

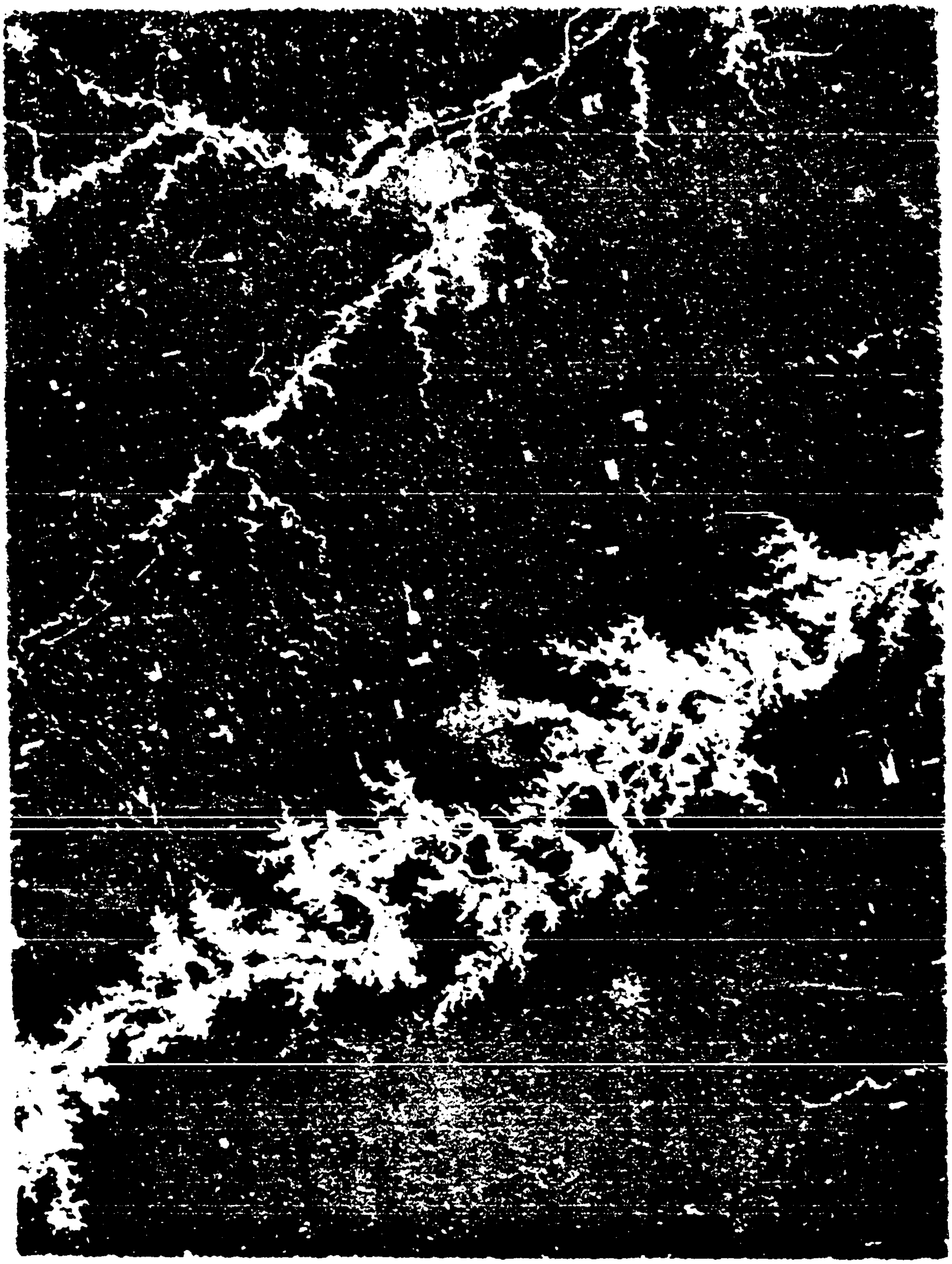
Township	SADE	ASCS 1965 photographs 1:20,000	SADE - ASCS / SADE	Average of remaining methods	SADE - Av. / SADE
	ha	ha	%	ha	%
Pilot Mound + Dodge	2705.2	2625.2	3.0	2472.4	8.6
Yell + Des Moines	2616.4	2620.4	-0.2	2659.2	-1.6
Marcy + Worth	3001.2	3005.6	-0.1	2826.8	5.8
Cass + Douglas	2270.8	1899.2	16.4	2000.0	11.9
Totals	10593.6	10150.4	4.2	9958.4	6.0

January 4, 1973.

Only Sections 10 and 15 in Worth Township were available as ground truth on forested areas in Boone County. Given the size of the resolution elements on the SADE data, that ground truth does not encompass an area sufficiently large to perform reliable correlations with estimated areas. Thus, the only possible way to correlate the results of the classification performed by ADD is to compare it to other estimations, mentioned in the previous paragraph.

Results of the comparison show close agreement among the different estimations. The highest difference observed was 16.4% for the Cass and Douglas Townships when the ASCS at scale 1:20,000 was used as an

Figure 20. Black and white enlargement of MSS band 7, covering a portion of central Iowa on January 4, 1973



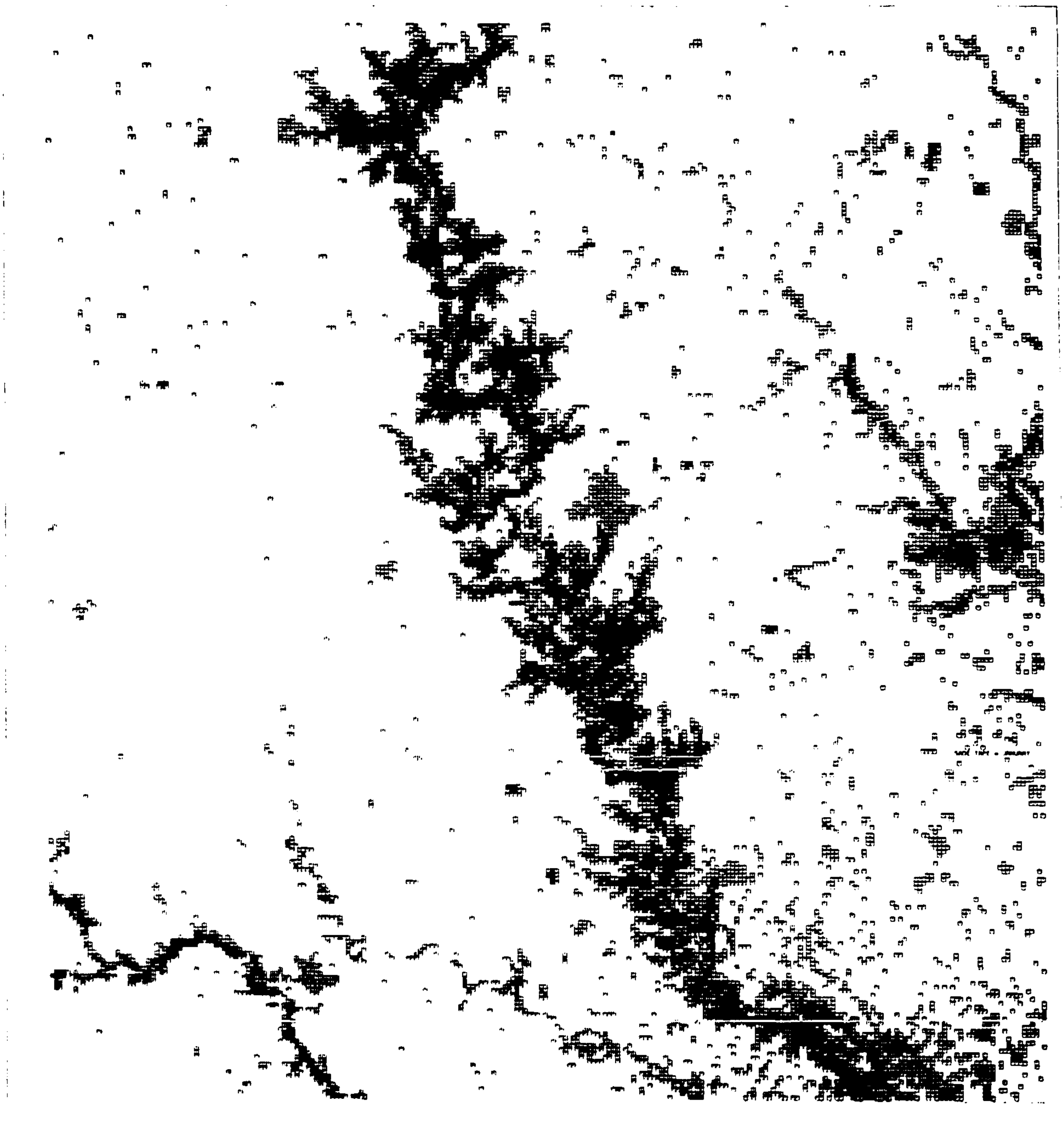
individual comparison. The forested area estimated from SADE data for the whole county is very similar to that obtained by Thomson. Some of the quantitative evaluations were performed by Thomson on January 4 imagery but on MSS 5, instead of the MSS 7 used here. He pointed out, all four available bands appeared to be equally usable for that purpose, and small differences might arise between estimates obtained from different bands.

The computer printout from which the reported estimates were obtained is shown in Figure 21. Comparison of this computer-produced map with a January imagery enlargement, performed with the aid of the Zoom Transfer Scope, confirmed the very close resemblance between them.

The digitizing process for the January imagery with the SADE system appeared correct and the results obtained are encouraging. The size of their resolution elements seems to be an advantage when highly contrasted features are displayed on the imagery. This enables a fast and relatively inexpensive county-size inventory and a small map. But, as it was stated before, the area encompassed by a resolution element can be also an important source of errors when irregular and/or small homogeneous areas are mapped.

Direct analysis performed on the original LANDSAT-1 tapes would probably provide a more accurate procedure for area measurement purposes. The number of resolution elements per mile provided by the satellite results in much higher precision than does the approximate 7 resolution elements per mile provided by the digitized 70 mm satellite imagery. This reflection is valid for all the other digitized imagery.

Figure 21. Computer-produced map showing the distribution of forested lands in Boone County, Iowa



Species identification on this imagery might not look very promising; further comparisons of the satellite imagery with false color infrared photography, as suggested by Carlson et al. (1974) should be helpful and subgroups delineated within each cluster group by the ADD program also should be helpful for the same purpose.

Yield Estimates

Corn yields

The model proposed by Thompson (1969a) for estimating average yield over relatively large geographical areas is based on departures of climatological parameters from average weather conditions. According to the model, corn yields in Iowa are associated with mean air temperatures occurring during the months of June, July, and August during each corn growing season, with pre-season precipitation from September to June, and precipitation recorded during the months of July and August. Departures of these parameters from normal values are most important in determining final corn yields, according to the model.

Corn yield per hectare for central Iowa was calculated using the following equation:

$$\begin{aligned} Y\ (\text{bu/A}) = {} & 43.117 + 0.7885X_1 + 0.4396X_2 - 0.0355X_2^2 + \\ & 0.4569X_3 - 0.2371X_3^2 + 1.7454X_4 + 0.5610X_4^2 + \\ & 0.2317X_5 - 0.2810X_5^2 + 0.0698X_6 - 0.4338X_6^2 - \\ & 0.6684X_7 - 0.1216X_7^2 + 2.7749X_8 + 0.0666X_8^2 \end{aligned}$$

Values for the X_i variables during the 1973 season were provided by the model's author. They were:

X_1 = technology factor measured in years from 1930 to 1960 = 24.428

X_2 = departure from normal pre-season precipitation = -0.01

X_3 = departure from normal June temperature = -1.2

X_4 = departure from normal July precipitation = 2.09

X_5 = departure from normal July temperature = -0.626

X_6 = departure from normal August precipitation = 0.039

X_7 = departure from normal August temperature = 0.428

X_8 = technology factor measured in years from 1961 to 1973 = 2.7749

A yield of 7107.8 kg/ha was obtained solving the above equation and converting the result to metric units.

Corn yields estimated accordingly for Boone County townships are given in Table 14 for areas estimated from corrected and uncorrected SADE data. Approximately the same range of overestimates and underestimates observed for the estimated areas from both corrected and uncorrected are found in that table. The total corn production estimated for the whole county was slightly overestimated by 13.6% applying the model to the areas estimated from the corrected data and by 11.9% using the uncorrected data. Considering that total corn areas were overestimated by 15.8 and 15.1%, respectively (Tables 10 and 12), the slight decrease on the overestimates is due to the yield per hectare value provided by the model being somewhat smaller than the average yield per hectare obtained from the Crop Reporting Service data (7107.8 kg/ha versus 7358.9 kg/ha).

Table 14. Corn yields on Boone County, estimated applying two methods to corrected and uncorrected SADE data and compared to Crop Reporting Service information

Township	CRS tons	Thompson's method				Shaw's method			
		Corrected SADE-tons	SADE-CRS / SADE	Uncorrected SADE-tons	SADE-CRS / SADE	Corrected SADE-tons	SADE-CRS / SADE	Uncorrected SADE-tons	SADE-CRS / SADE
Grant	28,279	32,684	13.5	38,992	27.5	36,288	22.1	43,831	35.5
Pilot Mound	12,195	17,772	31.4	22,745	46.4	19,732	38.2	25,568	52.3
Dodge	23,666	26,247	9.8	34,577	31.6	29,141	18.8	38,867	39.1
Harrison	27,447	29,465	6.8	35,283	22.2	32,714	16.1	39,662	30.8
Amaqua	29,975	23,564	-27.2	26,277	-14.1	26,164	-14.6	29,538	-1.5
Yell	15,645	17,629	11.2	19,319	19.0	19,573	20.1	21,716	28.0
Des Moines	21,106	22,456	6.0	23,840	11.5	24,933	15.3	26,799	21.2
Jackson	31,199	33,973	8.2	36,590	14.7	37,718	17.3	41,131	24.1
Beaver	29,239	27,142	-7.7	19,814	-47.6	30,134	3.0	22,272	-31.3
Marcy	30,249	33,720	10.3	27,160	-11.4	37,440	19.2	30,531	0.9
Worth	12,690	18,809	32.5	16,246	21.9	20,883	39.2	18,262	30.5
Colfax	25,931	36,691	29.3	32,987	21.4	40,735	36.3	37,081	30.1
Union	30,171	33,720	10.5	29,209	-3.3	37,440	19.4	32,833	8.1
Peoples	36,706	37,583	2.3	30,268	-21.3	41,727	12.0	34,024	-7.9
Cass	7,567	11,549	34.5	9,360	19.2	12,824	41.0	10,521	28.1
Douglas	6,604	16,091	59.0	13,810	52.2	17,866	63.0	15,523	57.4
Garden	31,048	43,553	28.7	37,155	16.4	48,357	35.8	41,766	25.7
Totals	399,717	462,648	13.6	453,632	11.9	513,669	22.2	509,925	21.6

Yield estimates were also obtained using the equation developed by Shaw (1974) for corn crops in Iowa:

$$Y(kg/ha) = 9118.6 - 90.3X$$

The accumulated weighted moisture-stress index X measured on one site on the east edge of Boone County amounted to 12.5 during the 1973 growing season and thus a yield of 7989.8 kg/ha was estimated by entering that value in the above equation. Obviously this value being higher than that provided by Thompson's model, all production estimates have to rise accordingly, and this is shown in Table 13. A final overestimate of about 22% was obtained for yield estimates calculated from modified and unmodified SADE data.

Thompson's model was in closer agreement with the Crop Reporting Service information than Shaw's model. The usefulness of both approaches is evident though, especially when considering that the Crop Reporting Service information to which the estimates were compared, may be in error too. Accurate area estimates are crucial factors in using either of the two models. The estimates given here are based on point values.

Both models will allow yield predictions well in advance of harvest time. Using Thompson's approach, yield forecasts are possible immediately after August climatological data are gathered, provided adequate satellite imagery have also been collected by that time. Shaw's seasonal moisture-stress index is calculated for a 85-day period before and after silking. The identification and location of each crop field on satellite imagery very early in the growing cycle would be an advantage, since it might be possible to check areas where spectral anomalies begin to appear on satellite imagery or ground truth information obtained later during the season. These were conditions cited by Morain (1974) as contributing to their remarkable 99% identification of wheat acreage in Kansas and their yield estimates being within 5% of the official statistical total for the area they studied.

Thompson's approach was also used to estimate soybean yields in Boone County. A yield of 2245.7 kg/ha was obtained solving the following equation and converting to the metric system:

$$\begin{aligned} Y\ (\text{bu/A}) = {} & 0.1527 + 0.4069X_1 + 0.2481X_2 - 0.0305X_2^2 + \\ & 0.2994X_3 - 0.0297X_3^2 + 0.5623X_4 + 0.2432X_4^2 + \\ & 0.3894X_5 - 0.0771X_5^2 + 0.2472X_6 - 0.0638X_6^2 - \\ & 0.1885X_7 - 0.0120X_7^2 \end{aligned}$$

where the X_i variables are the same previously mentioned for corn crops.

The yield per hectare calculated from the above equation was applied to area estimations obtained analyzing corrected and uncorrected SADE digital data and the results are shown in Table 15. All underestimates observed in both soybean crop area estimates (Tables 9 and 11) were more pronounced when yields were determined. That is understandable, since the Crop Reporting Service average yield per hectare is larger than the yield per hectare estimated by Thompson's equation, 2505.9 kg/ha versus 2245.7 kg/ha. Total productivity values for the county were about 20% lower than that determined by the Crop Reporting Service.

Table 15. Soybean yield estimations from corrected and uncorrected SADE data compared to Crop Reporting Service information

Township	CRS tons	Corrected SADE-tons	SADE-CRS / SADE %	Uncorrected SADE-tons	SADE-CRS / SADE %
Grant	7,750	6,914	-12.1	4,709	-64.6
Pilot Mound	3,837	3,988	3.8	2,299	-66.9
Dodge	6,867	6,124	-12.1	3,314	-107.2
Harrison	7,164	4,259	-68.2	2,254	-217.8
Amaqua	9,726	10,055	3.3	8,983	-8.3
Yell	3,302	3,875	14.8	3,225	-2.4
Des Moines	6,214	4,982	-24.7	4,397	-41.3
Jackson	9,268	6,203	-49.4	5,166	-79.4
Beaver	8,499	9,174	7.4	11,270	24.6
Marcy	8,040	6,451	-24.6	8,313	3.3
Worth	3,912	3,276	-19.4	3,973	1.5
Colfax	9,106	6,903	-31.9	7,845	-16.1
Union	8,519	8,688	1.9	9,876	13.7
Peoples	8,608	5,886	-46.2	7,978	-7.9
Cass	2,423	1,164	-108.2	1,796	-34.9
Douglas	1,690	1,615	-4.6	2,254	25.0
Garden	8,824	5,310	-66.2	7,097	-24.3
Totals	113,749	94,867	-19.9	94,749	-20.0

Acreage and yield predictions do not consider differences in crop variety, length of growing cycle, or quality of the final product harvested. In the present work, not even crop diseases or deficiencies were considered.

The capability of forecasting area and yields with acceptable accuracy for crops in a given region will benefit agricultural activities at all levels of decision starting at the farm level since primary producers will be able to know well in advance what they can expect from their activities, how the market will be likely affected by the input of the season's agricultural products, and thus they would be able to decide, within certain limits, what final fate of their products would benefit them more. Storage and transport resources would also be more efficiently used.

Soil Classification

Soil landscapes are visible on satellite imagery. They exhibit a characteristic surface geometry such as relative frequency of streams, and a characteristic surface composition given by the particular combination of crops and the sizes and shapes of the fields on which they are grown in a region.

Skylab imagery (June, 1974) was digitized and stored on the SADE magnetic tape. These data were analyzed as a possible way for generalized soil mapping as opposed to detailed soil mapping.

The original imagery is presented in Figure 22. Hydrology and vegetation patterns shown on the photograph seem to delineate regions on which different soil associations are present. The clustering

Figure 22. Skylab imagery covering Mills County, Iowa

algorithm of the ADD nonsupervised program produced the computer printout shown in Figure 23.

Soil maps are an integral part of any agricultural planning. Preparation of conventional soil maps for a county presently takes several years depending on the size of the county, the complexity of the soils present in the area, and many other factors. Obviously, satellite imagery will not eliminate the need for the soil scientist to traverse the landscape examining the soil at suitable intervals, but it can ease the work to be performed and maybe diminish the period of time required to complete it. This procedure also can be used in less accessible areas.

The computer-produced map shows remarkable resemblance to the photograph from which the digital data used to prepare the map were derived. Some features presenting narrow configuration appear to have been partially missed by the clustering technique used, but it has to be stated that in the computer map, only alternate pixels were printed so as to reduce the size and cost of the map. This means that only 50% of the total number of pixels were assigned a symbol and is probably the reason why some narrow features are not seen on the computer map.

The general soil map seen in Figure 24 confirms the usefulness of the Skylab imagery for soil mapping purposes and the SADE system which digitized it. The soil association areas numbered on the general soil map and their characteristics as they relate to the patterns on the general soil map are very briefly presented next.

1. Haynie-Albaton-Onawa association: level or nearly level, stratified silty and clayey soils that are well-drained to poorly drained and formed in alluvium on the Missouri River bottom lands.

Figure 23. Computer-produced map obtained from Skylab imagery covering Mills County, Iowa, digitized by the SADE system

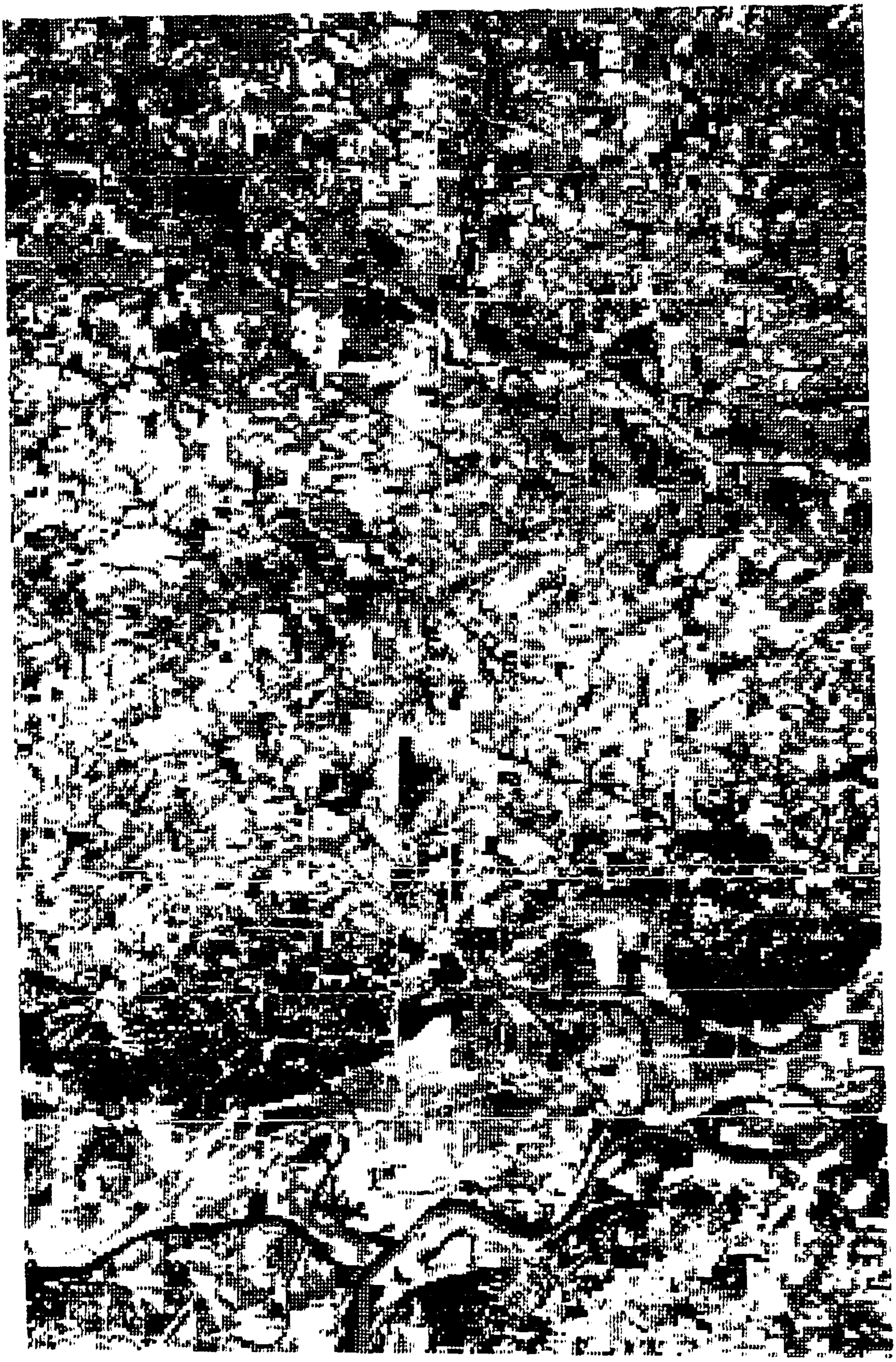


Figure 24. General soil map of Mills County, Iowa

2. Keg-Salix-Luton association: level or nearly level, dark colored, silty and clayey soils that are well, moderately well, and poorly drained and formed in alluvium on the Missouri River bottom lands.

3. McPaul-Napier-Moville association: level to gently sloping moderately dark to dark colored silty soils that are well, well to moderately well, and moderately well over somewhat poorly drained and formed in local alluvium on the Missouri River bottom lands.

4. Ida-Hamburg association: moderately sloping to very steep, silty soils that are well-drained and formed in loess.

5. Ida-Monona association: gently sloping to steep, silty soils that are well-drained and formed in loess.

6. Napier-McPaul association: level to gently sloping silty soils that are well-drained and formed in alluvium along the small upland streams.

The unnumbered soil association areas result from a very old, outdated map and are presently being surveyed for classification purposes.

The digital information used to prepare the computer-produced map was divided into three levels of symbol intensity, only. The potential for subdividing those three levels on several sublevels lies in the nonsupervised program. It is considered that smoothing or filtering techniques could provide means for refining the mapping obtained here. This was not attempted in the present work. The nonsupervised computer program was one of the latest developments of the research and so future work will have to be done to effectively aid the preparation of soil association maps with satellite imagery. Also, incompleted was a soil mapping of a central Iowa county, for instance Guthrie County, which would have been easily obtained from the January 4 snow-enhanced imagery stored on the magnetic SADE tape or from the original LANDSAT-1 digital tape now available.

SUMMARY

The purpose of this study was to continue investigations, already initiated at Iowa State University, concerning the feasibility of using data collected by the LANDSAT-1 satellite (formerly ERTS-1) in soils, forestry, and crops research.

Acquisitions were made of bulk, computer compatible tapes and photographic material collected by the satellite for a scene in central Iowa on May 10 and August 26 during the 1973 crop-growing season. Spectral bands free of clouds and showing the highest possible contrast among ground features were selected. Those were multispectral scanner bands 5 and 7 on August 26 and band 7 on May 10.

In addition to the satellite data, the National Aeronautics and Space Administration (NASA) provided low-level imagery which was used to correlate what was present on the ground surface with features perceivable on the LANDSAT-1 imagery.

Information stored on the LANDSAT-1 magnetic tapes was extracted and registered. A working magnetic tape was produced to facilitate handling of the selected data over an area in part of which a training site was established. That training site encompassed twelve sections in Colfax Township and two sections in Worth Township. Both sites were located in Boone County.

Initial visual evaluations of the data were performed to acquire knowledge concerning the characteristics of the digital responses yielded by the land-use categories which were evident on the imagery. That knowledge permitted the development of several schemes for land-use

classification. Multispectral, temporal classifications were performed on registered and nonregistered data. In order to incorporate additional imagery into the analyses, January 4, 1973 and July 2, 1973 images were digitized, together with the ones already mentioned, making use of the facilities provided by the SADE system available at South Dakota University.

Initial classifications were visually performed. Anomalies were apparent in the digital values provided by the SADE system. Values lower than expected were observed in the northeastern corner of Boone County on August MSS 7 data, while higher than expected values were observed in the southwestern corner. The need for an objective classification procedure led to the development of an automatic, nonsupervised, clustering algorithm which was called ADD, acronym for Analysis of Digital Data. Results obtained using the different classification procedures in the training site were compared to area estimates derived from low-level imagery.

Yield models developed by Shaw (1974) and by Thompson (1969a) made it possible to estimate corn crop yields in Boone County based on the area estimates provided by the land-use classifications. Similarly, a model proposed by Thompson (1970) permitted estimation of soybean crop yields in the same county. Those estimations were compared to pertinent statistical information provided by the Iowa State Crop Reporting Service.

Areas occupied by forested lands in Boone County were estimated by applying the ADD program to January 4 SADE data. Due to the lack of ground truth information, the results were compared to previous available estimates.

Finally, the usefulness of a photograph taken by astronauts aboard the Skylab mission encompassing Mills County, was investigated as a possible source of information for general soil-mapping purposes. The ADD program classified digital data obtained from the Skylab image by the SADE system. Results of the classification were compared to the original photograph with the aid of a Bausch and Lomb Zoom Transfer Scope and to a general soil map of Mills County.

The following results were reported:

<u>Area estimates</u> Area estimates obtained in the training site from registered imagery (May MSS band 7 and August MSS bands 5 and 7) were about 80% correct for soybean and corn crops. The percentage of resolution elements classified as corn or soybeans which actually did not correspond to any of those crops, was compensated for by those erroneously assigned to other categories, when in fact they were obtained over corn or soybean crops. Disregarding misclassifications originated by both types of errors, overall recognitions were 98.6% and 102.5% for corn and soybeans, respectively. Estimates for other land-use categories were less accurate due to the small number and/or irregular shapes of fields which were available within the training site. Area estimations performed on densely forested areas for which ground truth data were available (Sections 10 and 15, Worth Township) resulted in forest lands being underestimated by about 5% and pasture fields by 22.5%. These results are considered adequate considering the uncertainties arising from the relatively small area classified and from section registration difficulties in the computer printout. Some resolution elements in heavily forested areas were wrongly assigned to the corn-

crops category. Previously, forests were misclassified within corn fields. When the recognition procedures were applied to the entire Colfax Township, corn-crop areas were overestimated by less than 4% and soybean-crop areas by less than 8%. These figures gave support to the assumption that both types of errors made when classifying resolution elements, tend to compensate each other.

Good agreement between digital field acreage estimates obtained in the training site and those obtained from low-level images were observed. An overall $R^2 = 0.98$ was obtained.

Land-use recognition performed without registering the selected imagery improved correct identification for all categories except corn, with respect to the classification made on registered data. Correct identification of soybean crops amounted to 88.7%, but was still low for the remaining categories. The correct distinction between major crops, corn and soybeans, is a crucial one. Any modification introduced in the visual classification procedure, intended to improve the detection of one of them, invariably resulted in lowering the accuracy obtained in the recognition of the other.

The classification approach requiring no registration, when applied to SADE data modified to correct the apparent anomalies present on August MSS 7 dat, resulted in about 7% underestimation of the entire areas occupied by soybean crops in Boone County, with some severe underestimates for particular townships ranging from 27 to 91%. A 15.8% overestimation was obtained for corn crops in the same area, with some severe overestimations ranging in value from 32 to 62%.

Area estimates obtained in the same area using unmodified SADE data and the ADD computer program resulted in a slight underestimation for soybeans over the entire county (6%). Serious underestimates ranged from 44 to 189%, confirming the assumption that something was wrong with the digital information corresponding to August MSS band 7 and possibly with the MSS band 5. Corn crop areas for the whole county were 15% higher than those reported by statistical source. The highest overestimate for individual townships this time was 56.5%, and the lowest underestimate was 38.5%.

Detection and estimation of forested areas in Boone County resulted with values very close to estimates used with other methods. Over a total of about 10,000 hectares considered to be occupied by forested areas in that county, the ADD program gave an overall value which was within 4 to 6%. Areas were estimated for individual townships and paired, encompassing townships located on both sides of the Des Moines River. Areas estimated by ADD for Cass and Douglas Townships exceeded by 12 to 16% the values provided by the other estimations, being by far the highest disagreements found in the comparison. These disagreements could have been due to uncertainties in the location of the townships on the computer-produced map.

Results obtained from the August MSS 7 data with the ADD program in the 12-section area in Colfax Township showed a 90.9% correct identification of soybean crops. Out of a total of 1146.7 hectares, 987 hectares of soybean crops were correctly identified. Equally high degrees of accuracy were obtained for oats (90.8%) and alfalfa (99.2%). Pasture fields were overestimated by almost 30%.

Errors on the recognition and area estimation procedures used on this research may have resulted from inherent characteristics of the imagery used. Proper timing of temporal analyses in relation to growth and development of the crops to be identified is very important. For instance, the May 10 image was expected to discriminate between bare soil and actively growing vegetation. However, the wet spring delayed plowing activities and some fields were later planted to soybeans. If late May imagery had been available, all areas to be corn or soybeans would have been plowed enabling a more accurate discrimination.

Fields with small dimensions and/or irregular shapes offer great possibilities for misclassification and inaccuracies in area estimates. They can be either over- or underestimated. The multispectral scanner integrates the radiation being reflected or emitted by the ground enclosed within its instantaneous field of view. If the ground area being sensed is composed of dissimilar features, it is difficult to determine to which of the features present, the measured radiation has to be attributed.

<u>Yield estimates</u> Yield estimates for corn crops obtained using Thompson's model were very much influenced by area estimates. Approximately the same range of overestimates and underestimates found on corrected and uncorrected SADE data were found for yield estimates. The corn production for the whole county was overestimated by 13.6% when the model was applied to corrected data and by 11.9% when applied to uncorrected data.

Yield estimates obtained using Shaw's equation resulted in values about 22% higher than those provided by statistical sources using either modified or unmodified digital data. The yield per hectare calculated by Shaw's equation was slightly higher than that obtained from Thompson's model. This may be due to differences in the weather data base used in each model. This circumstance explains the higher overestimation which resulted using Shaw's model. Both models will allow field predictions well in advance of harvest time provided adequate satellite images have also been collected by that time.

The soybean yield estimate obtained with Thompson's model was 20% lower for the entire Boone County than the yield reported in the statistical information. Some important underestimations observed in area estimates from corrected and uncorrected data were more pronounced when yields were determined. The yield per hectare corresponding to Boone County in the Crop Reporting Service information was larger than that calculated by the model.

<u>Soil classification</u> The computer-produced map obtained for Mills County shows remarkable resemblance to the Skylab photograph. The usefulness of the ADD program applied to general soil mapping is obvious, even more when considering that only one photograph was used. Several photographs taken on different dates should be more helpful in aiding the task of identifying soils.

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